An Analysis of Hospital Behavior in Florida: 1990-1993

By

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An Abstract of
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Abstract

This dissertation uses several methods to find out why hospital margins are higher in more concentrated markets. According to the structure-conduct-performance paradigm, margins are higher in more concentrated hospital markets because concentration facilitates successful collusion. Alternatively, Demsetz (1973, 1974) argues that margins are higher in more concentrated markets because large market share firms have lower costs arising from their superior efficiency. To distinguish between these competing hypotheses, I estimate conjectural elasticities for 185 hospitals using panel data from Florida hospitals over the period 1990 to 1993 and test for competitive, collusive, and Cournot behavior, respectively. Probit models identify the factors that influence hospital behavior. Finally, to ascertain the effects that hospital behavior and market structure have on pricing, I also estimate a hospital price function.

Although I find evidence that Florida hospitals engage in cooperative behavior, the excess capacity in Florida hospital markets and the uncertain federal hospital merger policy suggest that this behavior most likely represents joint venture activity rather than an explicit attempt to restrict output below the competitive level. Market structure, moreover, does not have the expected effect on hospital behavior. Indeed, the probit regressions reveal, in contrast to the structure-conduct-performance paradigm, that market concentration actually reduces the likelihood of cooperative behavior. Instead, small, rural hospitals are most likely to behave cooperatively, implying that such behavior is necessary for these hospitals to survive in a managed care environment. Most important, I find no evidence that increased market concentration results in higher hospital prices. Hospital behavior, furthermore, has no impact on the prices that a

hospital receives. These results indicate that federal and state antitrust authorities should allow Florida hospitals to continue to reduce their excess capacity through joint ventures and mergers. Protection from federal antitrust prosecution under the Florida Hospital Cooperation Act should facilitate this effort.

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CHAPTER ONE

Introduction and Literature Review

I. Introduction

Recent studies on hospital competition find that, with the emergence of managed care networks, hospital margins are higher in more concentrated markets, consistent with the standard industrial organization paradigm [Dranove, *et al.* (1993)]. The hospital competition literature, however, does not explain the causality of this relationship, which may stem from either collusion or large hospital efficiency. The standard structure-conduct-performance paradigm predicts a positive relationship between profitability measures and market concentration because concentration facilitates collusion. The differential efficiency hypothesis that Demsetz (1973, 1974) introduces, conversely, argues that there is a positive relationship between profitability and concentration because more efficient, low cost firms gain market share.

It is important to distinguish between these two hypotheses for the hospital industry because each suggests a very different government policy toward mergers. Proponents of the collusion hypothesis support a strict merger policy for hospitals, arguing that concentrated hospital markets would facilitate cooperative behavior, thereby increasing the prices that hospitals receive. A key assumption in this argument is that hospitals compete primarily on price. Supporters of the efficiency hypothesis, by contrast, advocate a lenient merger policy for hospitals. They argue that concentrated hospital markets are efficient because high market share hospitals will have lower costs arising from both scale economies production and the partial avoidance of costly non-price competition.

This dissertation uses a variety of methods to distinguish between the efficiency and collusion hypotheses using data from 185 Florida hospitals over the 1990-1993 period. I estimate each hospital's conjectural elasticity and test for both Cournot behavior and collusion. Probit regressions identify those factors that increase the likelihood of these kinds of behavior. In addition price function estimates measure the effects of both hospital behavior and market structure on the prices that hospitals receive. I find evidence that Florida hospitals engage in cooperative behavior, but their behavior has no impact on the prices that they receive.

A study of competition in Florida hospital markets is important because the majority of the recent empirical work on hospital competition uses California data [Dranove, *et al.* (1993), Melnick, *et al.* (1992), Zwanziger and Melnick (1988), Robinson and Luft (1988)]. Analysis of Florida hospital markets is also timely, because Florida has initiated a market-based reform centered around the formation of purchasing alliances and provider networks. Eleven Community Health Purchasing Alliances (CHPAs) for the small group market became operational in May of 1994. These CHPAs will develop specific requests for proposals from networks of health care providers called "Accountable Health Partnerships," or AHPs. While CHPAs will not negotiate rates directly with an AHP, they will distribute AHP comparison sheets to their members, with information on prices, services, and quality.

This chapter reviews both the literature on hospital competition and the relevant empirical industrial organization literature. Chapter Two explores the appropriateness of applying a profit-maximization model to both for-profit and non-profit hospitals. Upon concluding that price competition among all hospitals has led non-profit hospitals to

behave like for-profit hospitals, Chapter Two closes with a theoretical model explaining the relationship between a hospital's net margin and its market share. Chapter Three presents the empirical specification of this model. Chapter Four describes the data. Chapter Five estimates and tests the significance of the estimated conjectural elasticities. To discern which factors influence hospital behavior, Chapter Five also includes probit regressions, in which the results of the significance tests are the basis for the binary dependent variables. Price-function analysis ascertains if cooperative behavior enables hospitals to receive higher prices. The chapter concludes with a discussion of the policy implications of these results. Chapter Six compares Florida cross section results with those from studies on hospital competition in California. Chapter Seven concludes.

II. A Review of the Literature on Hospital Competition

Historically, hospitals were charitable institutions responsible for the care of the indigent population.[1] As such, they were exempt not only from taxation, but also from tortious litigation [Gray (1991) at 64)]. Nonetheless, these hospitals still accepted paying patients, distinguishing the American "charitable" hospital from its British counterpart [Stevens (1989) at 19]. As early as 1904, for example, approximately one-half of private non-profit hospital revenue came from paying patients [*Ibid.* at 23].

Between 1915 and 1920 concern over access fueled a compulsory government insurance movement. Upon the temporary demise of this movement, the first Blue Cross plans appeared in the 1930s, to improve hospital access for the middle class without

[1] Stevens (1989) provides a detailed history of the development of the U.S. healthcare system.

depending on compulsory government insurance. Predictably, improved access increased the demand for medical services, which in turn increased medical spending. By the mid-1960s the bundling of an employee's tax-exempt health insurance benefit with monetary compensation and the implementation of Medicare and Medicaid increased non-price competition among hospitals. Two main factors drive this form of competition.

1. Under traditional indemnity insurance plans with low co-payments and deductibles,[2] the patient is relatively insensitive to the cost of obtaining medical treatment.

2. Physicians, who influence both the demand for and the supply of hospital services, are insensitive to the costs of providing treatment when they are reimbursed on a fee-for-service basis.

Under these conditions hospitals compete on perceived quality, not price, to attract both physicians and patients. Increased non-price competition, therefore, increases the unit cost of providing medical services, as well as the quantity of medical services demanded. Although increasing the amenities available to both physicians and patients increases hospital costs, provision of these amenities will not necessarily affect clinical outcomes, although they enhance patient and physician satisfaction [Held and Pauly (1983), Robinson and Luft (1987)]. Even if the actual quality of care improves, it may be "higher than consumers would be willing to pay if required to pay full price" [Woolley and Frech (1989) at 61].

State laws further reduce hospital incentives for pursuing efficiency. Certificate of Need (CON) laws provide an artificial barrier to entry.[3] These laws result in higher

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[2] Under traditional indemnity insurance, the insured party may seek care from any provider and receives reimbursement for the provider's reasonable charges, less any deductible or co-payment.

[3] Joskow (1980) states:

hospital prices and fail to control hospital costs [Noether (1988)]. State insurance law that forbade third party payors from directing policyholders to a lower priced hospital further reduced the incentive for hospitals to compete on price [Dranove, *et al.* (1992) at 3)].[4]

I now review the literature on hospital competition. Overall, this work finds that, prior to the mid-1980s, hospitals located in less concentrated or more competitive markets had higher costs than those hospitals located in more concentrated markets. This finding led researchers to conclude that, during this time period, hospitals competed primarily on a non-price basis.

Robinson and Luft (1985) use 1972 data from 5,013 U.S. community hospitals and find that both average total cost per admission and average total cost per patient day are higher in less concentrated hospital markets. The authors control for population density and use a variety of measures to control for regional differences. In addition to regional dummy variables, the authors include the county median per capita income and the county level annual earnings of retail trade sector workers as regressors. They define the geographical market to be the fifteen mile radius around each hospital in the sample and measure the level of concentration using a series of dummy variables. Specifically, dummy variables identify hospitals with one, between two and four, between five and ten,

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> While the CON process varies from state to state, these statutes usually require that hospitals obtain approval from a state agency before building a new facility or modifying an existing facility when the associated capital expenditures exceed some specified amount . . . . [T]heir objective is to constrain hospitals from building facilities which are not "needed.". . . . [I]t appears that what the CON agencies are trying to do is enforce some concept of efficient utilization of plant and equipment on the hospital sector [p. 433].

[4] "Federal laws exempted Health Maintenance Organizations and self-funded insurance from these state restrictions" [Woolley and Frech (1989) at footnote 1].

and more than eleven neighbors. Monopolist hospitals are the excluded group. Both the average total cost per admission and the average total cost per patient day are approximately six percent higher for hospitals that have only one neighbor than those of hospitals with no neighbors. The cost differential grows as the number of neighboring hospitals in the relevant geographic market increases. Hospitals with two to four neighbors have costs approximately nine percent higher than hospitals acting as a monopoly in the local market, with the cost differential increasing to about 21 percent for hospitals with more than eleven neighbors. The authors also observe this relationship when they use a subset of 1,084 hospitals for which they have explicit case mix data.

In an extension of this study, Robinson and Luft [1987] find that in 1982 both average cost per admission and average cost per patient day are significantly higher in less concentrated markets. Although the rate of change in these costs over the 1972-1982 period does not vary systematically with market structure, the authors conclude that "the cost-increasing effects of non-price competition on costs were already well in place by 1972 and . . . the following decade was not one of major change in the hospital system (p. 3244)."[5]

Noether (1988) uses American Hospital Association Annual Survey data and Medicare data from 1977-1978 to estimate both price and cost equations. The dependent variable in the cost equation is total hospital accounting expenses, which includes payments to salaried personnel, benefits, depreciation, and taxes. She estimates price equations for eleven disease categories using the average charge per Medicare

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[5] It is also possible that this result reflects the monopsony power of large hospitals.

inpatient diagnosis.[6] Per capita income, population density, the percentage of the population on welfare, and the unemployment rate control for regional differences. She uses Standard Metropolitan Statistical Areas (SMSAs) to define hospital geographic markets and calculates hospital market share and the Herfindahl index as a percentage of the total available beds in the market. Although this measure of market share measures potential competition, current market share will be understated if a hospital has a low occupancy rate.

Noether finds a significant negative relationship between hospital concentration and expense per Medicare admission, which is indicative of non-price competition. Because there is no significant relationship between the average charge per Medicare inpatient diagnosis and hospital concentration, she concludes that non-price competition dominates price competition among hospitals.

Noether's results may be suspect for two reasons. First, the charge data represent only Medicare reimbursement. "Political considerations play an important role in determining prices paid by public payors such as Medicare and Medicaid. The price/concentration relationship for public payors is hence murky" [Dranove, *et al.* (1993)]. Second, political boundaries define her geographic markets. Creating geographic markets using arbitrary borders, such as either political boundaries or fixed distances, biases downward the estimated effect of competition on hospital behavior [Zwanziger and Melnick (1988)]. Similar to Noether's result, both the Florida Agency for Healthcare Administration (FAHCA) (1989) and Melnick, *et al.* (1992) find no

[6] Disease categories include congestive heart failure, fracture of neck and femur, and pneumonia.

relationship between price and concentration when they use counties rather than patient origin data to define geographic markets.

FAHCA (The Florida Agency for Healthcare Administration) conducted two related studies in 1989 and 1992. In general, the FAHCA results are consistent with those in the California and national studies. The 1989 study analyzes the relationship between average cost per adjusted admission,[7] average charge per adjusted admission, and market concentration for 195 general acute hospitals over the 1982-1988 period. Population density, real county income, and the aged population control for regional differences across the state.

Consistent with Noether's (1988) results, costs in the 1989 FAHCA study are significantly higher in more competitive markets and there is no significant relationship between charges and concentration when counties define geographic markets. When patient origin data define the geographic market, however, charges are significantly higher in more competitive hospital markets.[8] Because the coefficient on the Herfindahl index in the cost equation is smaller then the coefficient on the Herfindahl index in the charge equation, it appears that over the 1982-1988 period hospitals could pass on the cost increasing effects of non-price competition to third party payors [FAHCA (1989)].

The 1992 FAHCA study uses data from 1984 to 1990 and also concludes that Florida hospitals compete primarily on quality. Consistent with the 1989 study, the 1992 study finds both charges and costs to be higher in more competitive hospital markets.

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[7] Adjusted for outpatient visits.

[8] The effect of market structure on price is more pronounced when patient discharge data define geographic markets. In the charge equation the coefficient on the patient flow Herfindahl is twice as large as the coefficient on the county Herfindahl.

Increased hospital competition, however, appears to slow the rate of increase in both costs and revenue over the sample period.

The empirical results discussed thus far suggest that at least since the creation of Medicare in 1965, hospitals have competed primarily on a non-price basis. Theoretically, the implementation of the Medicare prospective payment system (PPS)[9] and the increased use of selective contracting[10] should encourage price competition among hospitals. As expected, more recent empirical work does provide evidence in support of the increased role of price competition in the market for hospital services.

Robinson and Luft (1988) use data on 5,490 U.S. hospitals from 1982 and 1986 to analyze the effect of market structure on hospital costs. Their dependent variable is the percentage change in average cost per admission between 1982 and 1986. Median family income, population per square kilometer, and the number of physicians per 1,000 population control for regional differences. The authors also express the independent variables as rates of change over the sample period.

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[9] The implementation of PPS is a radical change in the Medicare system. Prior to 1983 Medicare reimbursed hospitals retroactively (after the hospital provided the service) based on reasonable cost. PPS, by contrast, determines hospital payment before the hospital provides care. The hospital must then absorb any differential between payment and cost. Diagnosis Related Groups (DRGs) provide the basis for PPS. The formation of DRGs is a means of classifying patients according to their medical condition. The reimbursement rate is the same for every patient within a particular DRG. See Russell (1989) for a detailed description of the Medicare System.

[10] Melnick and Zwanziger (1988) at 3669-3670 define selective contracting as the "procedure whereby a third-party payor can legally exclude providers from their list of participating providers without significant threat of antitrust prosecution." In January 1983, California became the first state to allow selective contracting. By 1992 there were approximately 2,578 separate PPO networks in operation throughout the 50 states, the District of Columbia and Puerto Rico [Marion Merrell Dow (1993)]. These networks reimburse member hospitals in a variety of ways. In 1992, networks used per diem rates to reimburse 44 percent of the hospitals, while 41 percent of the hospitals received discounted charges, with discounts ranging from seven to 26 percent [*Ibid.*]

They find that in 1982 average costs per admission for hospitals in more competitive markets are 27.5 percent higher then for hospitals with a local monopoly.[11] For hospitals with more than eleven neighbors, this cost differential decreases to 23 percent by 1986. The authors conclude that although

> hospitals in more competitive local markets experienced significantly higher costs than did hospitals in less competitive markets. The competition-related cost gradient became less steep during the four-year period considered, ... This suggests that the cost- increasing effect of non-price hospital competition was diminishing in importance during this period . . . . (p. 2678).

Consistent with the results of Robinson and Luft (1988), Zwanziger and Melnick (1988) identify a structural change in 1983 concerning the relationship between costs and hospital concentration. Specifically, Zwanziger and Melnick analyze the relationship between total hospital expenses and hospital concentration using data on California hospitals over the period 1980-1985. An urban/rural dummy variable, as well as labor and non-labor price indices control for regional differences. These authors depart from earlier work by creating hospital geographic markets using patient discharge data.[12] To isolate the effects of selective contracting on the relationship between costs and concentration, the authors also control for the implementation of Medicare PPS, which occurred at roughly the same time that selective contracting began in California.

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[11] Following Robinson and Luft (1985, 1987), the authors measure concentration using a series of dummy variables to identify the number of neighboring hospitals with in a fifteen mile radius of each hospital in the sample.

[12] The authors create a hospital's geographic market using zip code areas (ZCAs). A geographic market includes a ZCA if at least three percent of the hospital's discharges for a service category come from that ZCA. The authors also ensure that a geographic market contains at least forty percent of a hospital's discharges for each service category. They classify a hospital as a competitor if three percent of its total discharges come from a ZCA that is in the geographic market of another hospital.

Consistent with earlier works on hospital competition, Zwanziger and Melnick find that the coefficient on the HHI is negative and significant for the years 1980-1983, indicating that during this period hospitals in more competitive markets had higher costs than did those in less competitive markets. They observe no significant relationship between costs and concentration, by contrast, in 1984 and 1985. They conclude, therefore, that there was a structural change in the nature of hospital competition in 1983, because the change in the slope of the coefficient on the HHI between 1983 and 1984 is significant and positive.

The results that both Zwanziger and Melnick (1988) and Robinson and Luft (1988) report imply that the implementation of selective contracting in California increased the importance of price competition relative to non-price competition.[13] Because of the apparent increased prevalence of price competition in hospital markets, more recent studies focus on the relationship between pricing under selective contracting and the level of hospital concentration. In general, these studies find that the prices that a hospital receives are higher in more concentrated markets.

Staten, Umbeck, and Dunkelberg (1988) analyze the relationship between pricing in a PPO contract and hospital concentration using 1984 data on hospital bids[14] for inclusion in the Blue Cross of Indiana PPO. To measure market structure the authors use the number of hospitals in a county and a dummy variable identifying hospitals with a

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[13] Some non-price competition, however, will still exist. Non-price competition is prevalent in oligopolistic markets. Most studies on hospital competition characterize the hospital market as an oligopoly [Noether (1988)].

[14] The hospitals submitted bids as a percentage of their most recent set of charges. The authors do not reveal whether hospitals bid individually for each service provided, or base their bid on the average charge for all services that they provide.

monopoly position in a county. Their main result is that there is a significant negative relationship between the size of the bid and the number of hospitals in a county. Specifically, a hospital with a monopoly position in the local market submits bids between six percent and eleven percent higher than those hospitals in more competitive markets. The authors conclude that selective contracting increases price competition among hospitals. The negative relationship between a hospital's bid and the number of hospitals in the county may not conclusively imply that there is price competition in hospital markets, however, because the authors do not control for possible case mix variations, hospital ownership, or regional differences across the state.

Melnick, Zwanziger, Bamezai, and Pattison (1992) identify three additional problems with the Staten, *et al.* (1988) study. First, Staten, *et al.* use the bid that the hospital submits to the PPO, rather than the actual contract price, as the dependent variable. Melnick, *et al.* note that the bid and the final contract price could differ significantly; so they use the per diem price that the hospital actually receives from the Blue Cross PPO of California as their dependent variable. Second, Staten, *et al.* use data from the Blue Cross of Indiana PPO at its inception. The Blue Cross PPO of California had been operating for five years, by contrast, before the sample period in Melnick *et al.*, therefore allowing for any kind of negotiation "learning curve." Third, Staten, *et al.* use county boundaries to define the relevant geographic market. This definition overstates the actual amount of competition in a large county, as all of the hospitals will not compete directly with each other. Melnick, *et al.*, following Zwanziger and Melnick (1988),.use patient discharge data, by contrast, to calculate geographic markets.

Using 1987 data from 190 hospitals in the Blue Cross of California PPO network, Melnick, *et al.* analyze the relationship between the price a hospital receives from the Blue Cross PPO and market concentration. The authors control for hospital costs but not for hospital case mix or population differences across the state. They find that the per diem price that a hospital receives from the Blue Cross PPO increases as hospital concentration increases. A hospital with a large share of Blue Cross subscribers in the local market, in addition, receives a higher contract price that increases even further as competition in the hospital market declines. These results are suspect for two reasons. First, they identify a relationship for only one, albeit large, payor from a single state. Second, and more important, the authors ignore the effect of hospital case-mix on price.

Dranove, *et al.* (1993), using 1983 data from 292 hospitals and 1988 data from 296 hospitals, analyze the relationship between both hospital prices and margins and hospital concentration in California. As a proxy for the Lerner index, the authors use the accounting margin [(net price- average total cost)/net price] on a market basket of hospital services as a dependent variable. The net price of the market basket equals net revenue/units of service, with net revenue equal to gross charges less deductions for contractual allowances, charity care, and bad debt. The authors define hospital geographic markets to include both urbanized areas, as the Bureau of the Census identifies them, as well as population centers of at least 5,000 that contain at least one hospital. They use 88 markets in their analysis. This study does not control for regional differences across the state, a hospital's teaching status or kind of ownership. The authors, moreover, exclude government hospitals from their sample.

The authors find that hospital margins on inpatient services for privately insured patients are higher in more concentrated hospital markets in 1988, but they find no significant relationship in 1983, the year in which selective contracting began in California. They also find a weak, positive relationship between net price and concentration in 1988. In 1983, by contrast, there is a highly significant, negative relationship between these two variables. These results, in conjunction with the findings of Zwanziger and Melnick (1988), who find a structural change in the relationship between costs and concentration, imply that price competition plays a greater role in hospital markets since the implementation and increased use of selective contracting by third-party payors.

One must interpret the results in Dranove, *et al.* with caution. In addition to the omitted independent variables that I mention earlier, the authors most likely understate margins because they reduce net revenue not only by contractual allowances but also by deductions for charity care and bad debt expense. Second, the results are not robust to changes in the dependent variable. The coefficient on the Herfindahl is near zero and insignificant when the authors use gross margin rather than net margin as the dependent variable. While the relationship between net margin and concentration is significant at the one percent level, the relationship between net price (with cost as a control variable) and concentration is significant at only the ten percent level. Third, the authors define hospital geographic markets using geopolitical boundaries rather than patient origin data. When Melnick, *et al.* (1992) use county borders to define geographic markets, the

relationship between price and concentration is not clear.[15] Zwanziger and Melnick (1988) state, furthermore, that using political boundaries or fixed distances to define geographic markets results in estimates of the effect of competition on hospital behavior that are biased downward. Surprisingly, Dranove, *et al.* report "slightly stronger" (p. 191) results when they define geographic markets based on county borders.[16]

Proponents of a rigorous antitrust standard for the hospital industry cite the results from both Melnick, *et al.* (1992) and Dranove, *et al.* (1993), arguing that their results are consistent with the structure-conduct-performance paradigm that industrial organization economists find in many inter-industry studies. There are three reasons, however, why more research analyzing the relationship between hospital prices and margins and market structure studies is necessary.

First, the majority of the recent empirical work on hospital competition uses California data [Dranove, *et al.* (1993), Melnick, *et al.* (1992), Zwanziger and Melnick (1988), Robinson and Luft (1988)]. Because California leads the nation in managed care penetration, the findings of the work just cited may be unique to California. For example, although enrollment in Florida HMOs increases 10.7 percent from 1992 to 1993, only 18.3 percent of the state's population belonged to an HMO [Marion Merrell Dow (1994)]. In California, by contrast, 36.4 percent of the population is enrolled in HMOs [*Ibid.*] The national average is 19.4 percent [*Ibid.*].

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[15] In one specification of the model, the authors find no significant relationship between price and concentration. In another specification the relationship is significant, but the coefficient on the HHI is less than one-fifth of its value when the authors use patient flow data to define geographic markets.

[16] The authors do not provide any details about these results.

Research by the Florida Agency for Healthcare Administration also illustrates the different levels of managed care development in Florida and California. As late as 1990 the relationship between hospital concentration and cost per admission is negative [FAHCA (1992)]. In California hospital markets, by contrast, there is no significant relationship between costs and concentration as early as 1984 [Zwanziger and Melnick (1988)]. These differences illustrate that research using data from states other than California, states which are in earlier stages of their managed care development, is necessary to better understand the nature of hospital competition.

Second, the relationship between hospital margins, prices, and concentration is not robust to changes in key variables. The definition of geographic market seems to affect the significance of the relationship. When Melnick, *et al.* (1992), Noether (1988), and FAHCA (1989) use geopolitical boundaries to define geographic markets, there is no significant relationship between hospital concentration and price. The relationship becomes significant, by contrast, when patient discharge data define hospital geographic markets [Melnick, *et al.* (1992)]. The choice of dependent variable also appears to matter. When Dranove, *et al.* (1993) use gross rather than net margin, the coefficient on the Herfindahl index is near zero and insignificant. In the 1992 Florida study, by contrast, there is a negative, significant relationship between both gross and net hospital charges and market concentration.[17]

Third, and most important, knowing the cause of a positive relationship between hospital margins and market structure is more meaningful than merely identifying

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[17] Notice that market definition may be driving this result. When counties define geographic market, the 1992 Florida study finds no relationship between either gross or net revenue and market concentration.

statistical significance. Recall that the results of Melnick, *et al.* (1992) suggest that market concentration facilitates collusion. The results of Dranove, *et al.* (1993), by contrast, allow for the possibility that efficient hospitals gain market share, thus driving the identified positive relationship between hospital margin and market concentration. It is important to distinguish between these two hypotheses because of the recent interest in hospital mergers by the Department of Justice and the Federal Trade Commission.[18]

There is some preliminary, indirect, evidence that suggests that the efficiency hypothesis best explains the observed positive relationship between hospital price-cost margins and market concentration. A case study analyzing the dynamics of hospital competition in California concludes that increased concentration in the hospital industry was necessary for the widespread viability of selective contracting and managed care networks [Starkweather and Carmen (1988)]. Pautler and Vita (1994 at 134) interpret Noether's (1988) finding of a negative relationship between costs and concentration but no significant relationship between charges and concentration, furthermore, as evidence that "efficient (low cost) hospitals gain large market shares, which increases measured concentration."[19] They also argue that Woolley's (1989) finding that hospital merger announcements increase the market value of rival hospitals indicates that the announced

[18] Dranove, *et al.* (1993) acknowledge that either market power or efficiency could explain the observed positive relationship, but they employ no rigorous test to distinguish between the competing hypotheses. When the authors control for market share, the positive coefficient on the HHI becomes smaller, but it remains highly significant. Harris (1988) shows that a positive market share coefficient and an insignificant coefficient on the Herfindahl is not conclusive evidence of leading firm efficiency. Geroski (1982), furthermore, suggests that models that include both market share and a measure of concentration are mis-specified.

[19] Noether's use of gross rather than net price as an independent variable, however, could be driving this result. When Dranove, *et al.* (1993) use gross rather than net margins as the dependent variable the coefficient on the Herfindahl is insignificant.

transactions "convey information to other firms about the existence of merger-related efficiencies" [Pautler and Vita (1994) at 136].[20] Section III now reviews the relevant industrial organization literature that more formally discusses the possible interpretations of a positive relationship between price-cost margins and market concentration.

III. A Review of the Literature Analyzing the Relationship Between Price-Cost Margin and Market Structure

The results of both Dranove, *et al.*(1993), and Melnick, *et al.*(1992) parallel those that industrial economists find in many manufacturing inter-industry studies. Surveys that review this voluminous literature, beginning with Bain's research (1951),[21] observe that the majority of these studies document a positive relationship between profitability and market concentration. Researchers commonly interpreted this result as a confirmation of the collusion hypothesis [Weiss (1974), Demsetz (1974)]. According to this hypothesis market concentration facilitates collusion. Even though the relationship between industry profitability and market concentration was not robust,[22] this research provides the basis for the structure-conduct-performance paradigm. According to this paradigm the

[20] Citing Vita and Schumann (1991). Woolley interprets his results differently, arguing that they best support the collusion hypothesis because he finds that antimerger announcements, such as an antitrust complaints, reduce the market value of rival hospitals.

[21] See Schmalensee (1989) and Weiss (1974).

[22] Both Demsetz (1974) and Schmalensee (1989) in their literature reviews, critique the early inter-industry studies. They observe that the identified positive relationship is often statistically weak, fails to hold up in time series studies, and often disappears altogether when researchers control for capital intensity, advertising intensity, and economies of scale. Weiss (1974), a proponent of the structure-conduct-performance paradigm, admits that the data that the inter-industry studies use is not perfect. He argues, however, that the research challenging the collusion hypothesis also suffers from similar methodological problems.

structure of the industry determines firm conduct, which in turn determines firm performance.[23] This hypothesis assumes that industry structure is exogenous, making a firm's behavior dependent on market structure.

Demsetz (1974, 1973) argues that the positive correlation between profitability and market concentration that the many inter-industry studies observe, reflects firm-specific effects rather than collusion. A key assumption in this hypothesis is that there are persistent efficiency differences among firms [Schmalensee (1987, 1985)].[24] Specifically, as a firm in an industry gains market share because of superior efficiency, arising either from economies of scale production (increasing returns to scale) or product innovation, the firm will earn economic rents. It is this large firm efficiency, rather than collusion, that drives the positive relationship between average industry profitability and concentration. It is important to realize, however, that this hypothesis does not necessarily assume price-taking behavior by firms [Schmalensee (1987)].

Demsetz tests his hypothesis by controlling for firm size. He uses 1963 industry-level Internal Revenue Service profit data for 95 industries. If the efficiency hypothesis is correct, there will be a positive correlation between profit rates and concentration only for large firms. He concludes that his results support the efficiency hypothesis because

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[23] See Martin (1993) or any standard industrial organization text for a detailed discussion.

[24] This hypothesis interprets efficiency broadly. Schmalensee (1985) states :

> Efficiency should not be interpreted in narrow process terms here. A product innovation may simply make a firm more efficient in the production of the Lancastrian characteristics [product attributes] it supplies to an existing market. . . . [I]t seems appropriate to think of nondramatic product innovations in efficiency terms for purposes of positive analysis of profitability" [p. 342, footnote 3]. See also Schmalensee (1987).

"most of the correlation between accounting profit rates and concentration can be attributed to firm size not market concentration" [1974 at 179].

Opponents of the efficiency hypothesis criticize on theoretical grounds Demsetz's conclusion that his results support the efficiency hypothesis because the findings are not inconsistent with collusion among larger firms [Weiss (1974), Martin (1988, 1993, Chp. 17)]. These researchers argue that large firms earn economic rent only if they cannot meet market demand by operating at their efficient capacity. If these firms restrict output, by contrast, they are exercising market power and creating a niche for less efficient firms [Martin (1993 at 489-90)]. Demsetz (1974 at 178) acknowledges this criticism but argues that the costs of moderately sized firms will be the upper limit at which the colluding firms can set prices. The market price with deconcentration, therefore, will be the same as the price under collusion.

Empirical studies employing Demsetz's methodology, however, do not replicate his results. Amato and Wilder (1988), using a less aggregated version of Demsetz's data,[25] find that none of the interaction terms combining firm size and concentration are statistically significant in a regression explaining class size profitability. According to the efficiency hypothesis, the interaction term should be positive for large firm size classes. Clarke, Davies, and Waterson (1984) test Demsetz's methodology using three digit Census of Production data from the U.K. They find that small firms have significantly higher margins in more concentrated industries and that there is no significant difference

[25] They use IRS industry-level data with twelve firm size classes instead of four.

between large and small firm margins in highly concentrated industries. These findings also support the collusion hypothesis rather than the efficiency hypothesis.

In spite of these criticisms of Demsetz's work, several papers try to distinguish empirically between the efficiency and collusion hypotheses. Amato and Wilder (1990 at 93) summarize this debate "in terms of differences in the relative importance assigned to firm and industry effects in explaining cross-sectional variation in profitability." Weiss (1974) suggests including both market share and concentration as independent variables, to discern the relative importance of firm and industry effects. A positive significant market share coefficient[26] and an insignificant concentration coefficient indicate the importance of firm-specific market power arising either from efficiency, product differentiation, or cost-reducing innovation [Ravenscraft (1983), Harris (1988)]. Not surprisingly, researchers find support for both hypotheses.[27]

Both Schmalensee (1985) and Amato and Wilder (1990) conclude that industry effects dominate any persistent inter-firm differences. Amato and Wilder use industry level Internal Revenue data from 1966 and 1975 to discern the relative importance of industry and firm effects. The unit of observation is the IRS asset size class, with the rate of return on assets as the dependent variable. The average market share of each size class in each industry represents firm effects, while industry-level dummy variables capture industry effects. The authors also control for advertising intensity, capital intensity, and minimum efficient scale. Amato and Wilder (1990) conclude that industry

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[26] Amato and Wilder (1988), however, argue against the use of market share as a proxy for firm efficiency. They contend that relative cost is a better measure of efficiency.

[27] There is also evidence that these hypotheses are complementary rather than mutually exclusive. See Peltzman (1977), Clarke, *et al.* (1984), and Martin (1988b)

effects are more important than firm effects in explaining inter-industry differences in profitability. When they omit the industry-level dummies from their model, no variable, including the four firm concentration ratio, is significant. When they include the industry-level dummy variables, by contrast, the concentration and minimum efficient scale variables become highly significant and the adjusted R^2 increases from .08 to .30.

Schmalensee (1985) tries to distinguish between industry, market share, and firm effects using 1975 Federal Trade Commission Line of Business data. He defines firm effects as those stemming from managerial advantages while market share effects arise from persistent efficiency differences among firms. Dummy variables capture managerial and industry effects. The dependent variable is the ratio of operating income to total assets, which measures the pre-tax rate of return on total capital. Based on analysis of the adjusted R^2 and F-statistics, Schmalensee concludes that industry effects dominate market share effects, while firm effects are nonexistent. Although he can reject the null hypothesis that there are no market share effects, market share effects explain only between .17 and .62 percent of inter-industry variation in accounting rates of return. Inter-industry effects, by contrast, account for between 18.84 and 19.29 percent of industry-level profit variability. In spite of these results he observes that approximately "80 percent of the variance in business unit profitability is unrelated to industry or share effects" (p. 350).

In contrast to the studies just reviewed, many researchers also find evidence that firm specific effects, rather than industry effects, are an important determinant of industry profitability. Shepherd (1972) uses firm-level data over the 1960-1969 period on 231 firms from the *Fortune Directory*, to analyze the relative importance of industry and

market share effects on variation in a firm's rate of return on equity. Firm size and advertising intensity capture the importance of entry barriers.

Shepherd concludes that market share is the primary determinant of profitability, because the coefficient on market share is highly significant and positive for the entire panel, as well as for various subsets of industries. The negative significant coefficient on the square of market share for certain subsets of data indicates that the effect of market share, moreover, may be convex rather then linear. The insignificant coefficient on the market structure regressor for the majority of industry groupings indicates that industry effects are not important in this data set in explaining variations in a firm's rate of return on equity.

Gale and Branch (1982) use Strategic Planning Institute product-line data over the period 1976-1979 to analyze the relationship between ROI (before-tax profits divided by equity) and market share and firm concentration . In a regression with only market share and the four-firm concentration ratio, they find that the coefficient on market share is positive and highly significant while the coefficient on concentration is negative and statistically insignificant.

Acknowledging that this relationship may result because of either higher prices or lower costs, the authors also estimate price and cost equations. In the price equation both the coefficients on market share and quality are positive. [28] They conclude, however, that high quality is more important than market share in determining price

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[28] Gale and Branch measure relative firm quality as the difference between the percentage of a firm's total sales that comes from products it rates as superior to those of the competition and the percentage of a firm's total sales that comes from products it considers to be inferior.

because the coefficient on market share is significant only at the ten percent level, while the coefficient on the quality variable is significant at the one percent level. In the cost regression for firms that sell differentiated products, by contrast, the coefficient on market share is significantly negative, while the coefficient on the quality variable is significantly positive. Comparing the relative magnitude of the market share coefficients in the price and cost regressions, they conclude that lower costs are the principal determinant of the market share-profitability relationship.

Consistent with the findings of both Shepherd (1972) and Gale and Branch (1982), Ravenscraft (1983) using 1975 Federal Trade Commission Line of Business data,[29] finds that market share is more important than the four-firm concentration ratio in explaining profitability. He defines profitability as the ratio of operating income to sales. In addition to documenting the relative importance of market share, he also tries to discern the source of this relationship by interacting market share with a measure of firm size, the advertising-sales ratio, and the R&D-sales ratio which reflect the effect of scale economies, market power arising from product differentiation, and superior innovative ability, respectively. Of these three interaction variables, only the coefficient on the R&D-sales ratio is insignificant, leading Ravenscraft to conclude that the effects of product differentiation and size best explain the market share-profitability relationship.

In sum, Shepherd (1972), Gale and Branch (1982), and Ravenscraft (1983) measure the relative importance of market share and industry effects by including both market share and concentration as regressors in the profitability equation. Other

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[29] The Federal Trade Commission refers to a line of business as a firm's operations in one of 261 manufacturing and fourteen non-manufacturing categories.

researchers, however, criticize models that include both market share and concentration as regressors. Geroski (1982) contends that such models are misspecified because conduct jointly determines both market share and profit-margins, regardless of their causes. In other words, "the structure performance model is equivalently an inter-industry model and an intra-industry model" [Geroski (1982 at 322)].

Harris (1988) argues, furthermore, that the results of Gale and Branch (1982) and Ravenscraft (1983) are not conclusive evidence against the collusion hypothesis. He contends that a significant market share coefficient and an insignificant concentration coefficient support the efficiency hypothesis only when products are homogenous and the regressors include a proxy for scale economies, which accounts for the negative, indirect effect of increasing scale economies on firm margins. He notes that unless the profitability equation includes a scale economies variable, "an insignificant relationship between the Herfindahl index and price-cost margins might be attributable to the output increases, price reductions, and declining margins associated with scale economies in production" (p. 272)]. A positive coefficient on the scale economies variable indicates that the concentration effect dominates the margin-reducing effect of scale economies.[30,31] According to this scenario increasing returns to scale production implies a concentrated market, which results in higher margins.

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[30] According to Harris's argument, Shepherd's (1972) interpretation of a negative size coefficient as evidence of X-inefficiency may instead reflect scale economies.

[31] Even with Harris's analysis, Ravenscraft's results still support the efficiency hypothesis. The coefficient on the scale economies variable is significantly negative, indicating that the scale economies effect is present. The insignificant concentration coefficient then shows that the scale economies effect is stronger than the concentration effect. Gale and Branch (1982) do not include a measure for scale economies as an independent variable.

There are also two offsetting effects of increased concentration on firm price-cost margins for differentiated products, notwithstanding the scale economies effect [Harris (1988)]. In a highly concentrated market, collusive arrangements are less likely to erode [Stigler (1964)]. This reduction in price competition, however, causes the firm's perceived own price elasticity of demand[32] to increase, causing margins to decline. Because of these two offsetting effects, an insignificant concentration coefficient may not provide conclusive evidence in support of the efficiency hypothesis for differentiated products.

Because of the ambiguous results of the work including both market share and concentration as regressors, researchers also try to distinguish between the collusion and efficiency hypotheses by estimating conduct parameters and testing for various kinds of firm behavior, such as Cournot or Bertrand, rather than merely interpreting the estimated coefficients on market share and concentration variables. These studies commonly use estimates of the conjectural elastcity to describe the average behavior within a particular industry. Table 1.1[33] provides examples of the estimated conjectural elasticities from Stalhammar (1991), Clarke, Davies, and Waterson (1984), and Applebaum (1982) and illustrates that the estimated conjectural elastcities differ substantially by industry. I now discuss each of these studies.

Clarke, Davies, and Waterson (1984) use industry-level U.K. data over the period 1971-1977 to estimate a net margin equation for 29 industries. They use estimated

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[32] Harris (1988) states: "The intuitive logic of this second, competing influence of concentration is analogous to the effect on margins of an increasing price elasticity of market demand- e.g., as a result of more or closer substitutes outside the relevant market" (p. 275).

[33] Section IV contains all tables pertinent to the analysis in this chapter.

coefficients from this regression to calculate each industry's conjectural elasticity.[34] The limiting values of this parameter are zero and one. A value of zero represents Cournot behavior, while a value of one indicates collusion. As expected, they find that behavior differs according to industry. Overall, the estimated conjectural elasticities range from .039 to .536, with a mean of .254. The estimated conjectural elasticity for the Shop and Office Fittings industry, for example, is .039, indicative of Cournot behavior. The Printing Ink and Telegraph and Telephones industries, by contrast, appear to be more collusive with estimated conjectural elasticities of .535 and .536, respectively.

Clarke, *et al.* also regress the estimated conjectural elasticities on both the four firm concentration ratio and the Herfindahl index. They find that the estimated coefficients on both the concentration ratio and the Herfindahl index are positive and significant at the one percent level. Based on these results they conclude that, in spite of the relatively low mean estimated conjectural elasticity, the collusion effect best explains the profitability-concentration relationship. The authors, however, do not provide, the statistical significance of the individual estimated conjectural elasticities. Because the significance of the estimated conjectural elasticities are more important than their numerical value, it may be more informative to focus on the relationship between the significance of a firm's conjectural elasticity and market concentration using a limited dependent variable model.

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[34] A firm's conjectural elasticity is the reaction it expects from its rivals in response to changes in its output. More specifically, firm i's conjectural elasticity equals $(dX_j/dX_i)(X_i/X_j)$ for all i and for $j = 1 \ldots \neq i \ldots N$.

Applebaum (1982) uses industry-level data in a study of four U.S. manufacturing industries (rubber, textile, electrical machinery, and tobacco) over the period 1947-1971, to estimate a system of equations including expressions for factor demand, market demand, and the aggregate profit maximization condition. She calculates an annual conjectural elasticity for each industry,[35] which is a function of exogenous input prices. The estimated mean conjectural elasticities range from .0186 in the rubber industry to .4019 in the tobacco industry and are significantly different from zero in only the electrical machinery and tobacco industries. Applebaum also tests for the degree of oligopoly power using a modified version of the Lerner index. This measure is a function of the industry conjectural elasticity and demand elasticity. She finds that the Lerner index is significantly different from zero in both the electrical machinery and tobacco industries.

In a more recent study, Stalhammar (1991) analyzes 67 Swedish manufacturing industries using plant level data for 1985. He estimates a price-cost margin with industry dummy variables and tests for Cournot behavior by calculating each industry's conjectural elasticity. The estimated conjectural elasticities are significantly different from zero in 32 of the 67 industries studied. Unfortunately, Stalhammar does not provide examples of these industries. He concludes that Cournot-like behavior best describes the manufacturing sector because the estimated conjectural elasticities average only .045 and range from .0001 to .190. In spite of this conclusion, he finds a statistically significant relationship between the Herfindahl index and an industry's estimated

[35] Applebaum defines the conjectural elasticity as the percentage change in total industry output given an output change by firm j.

conjectural elasticity, implying that higher levels of concentration facilitate collusion [Clarke, *et al.* (1984)]. Because the coefficient on the square of the Herfindahl index is significantly negative, Stalhammar also observes that the effect of concentration on behavior is nonlinear.

In a related paper, Schmalensee (1987) tries to distinguish more rigorously between the collusion and efficiency hypotheses and tests for combinations of these two kinds of behavior. He uses IRS size-class data for seventy minor manufacturing industries in both 1963 and 1972, to estimate an industry rate of return equation. He includes controls for both advertising and capital intensity. In general, the data do not conclusively identify any particular behavior. The estimated parameters, furthermore, are very different for each of the two years studied, in spite of their cyclical similarity. Schmalensee thus concludes that

> there is no support for use of [the two hypotheses or a combination of the two] . . . as maintained hypotheses in policy analysis or the study of individual industries. It would appear likely that the relative importance of collusion and differential efficiency vary considerably among industries and over time" [p. 420].

While the four studies just reviewed use industry-level data, other research uses firm-level data, in trying to capture the unique aspects of certain industries that an industry-level analysis masks. In contrast to the inter-industry analyses, these studies typically estimate the firm's conjectural variation, rather than its conjectural elasticity. Again, the results from this research are mixed.

Iwata (1974) uses data spanning the years 1956 to 1965 to estimate a market demand function and cost functions for two firms and two products (window glass and polished plate glass) in the Japanese flat glass industry. He uses these equations to obtain

measures of marginal cost for each firm and for the price elasticity of demand.[36] Using these estimates, he calculates each firm's conjectural variation for each quarter over the sample period. The estimated conjectural variations differ substantially between the two firms and between products and range from -.3 to .7. Tests to see if these estimates are significantly different from zero in the window glass market reveal that Cournot behavior best describes this product's market.[37]

Roberts (1984) estimates conjectural variations[38] for 52 firms in the U.S. coffee roasting industry and tests for Cournot, dominant firm, and price-taking behavior. He uses the variable profit function (revenue less variable cost) and Hotellings Lemma to derive output supply and input demand equations, which include an expression for profit-maximizing marginal revenue. It is the expression for marginal revenue that contains the firm's conjectural variation. He then estimates the parameters of the profit function and conjectural variations. Because he uses cross sectional data, he calculates conjectural variations only for designated benchmark firms.[39] For the remaining firms he calculates the conjectural variation as weighted averages of the benchmark conjectural variations.[40]

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[36] Iwata uses each firm's accounting data from which he estimates input demand functions. He substitutes these functions into the cost equation and differentiates to arrive at a measure of marginal cost. He also assumes homogeneous products.

[37] Iwata tests the hypotheses only for the estimated conjectural variations from the first quarter of 1956.

[38] Firm i's conjectural variation is (dq_j/dq_i) and represents firm i's belief concerning how firm j will respond to changes in i's output.

[39] He designates the four largest firms, the fourteenth largest firm, and the smallest firm as benchmarks.

[40] He bases the weighted average on the estimated conjectural variation of the two nearest benchmark firms, one with a larger output level, the other with a smaller output level.

Roberts rejects, at the one percent significance level, price-taking behavior for the two largest firms. Although these firms produce 55 percent of total industry output, he concludes that they exercise little market power because their estimated marginal revenues are only 5.5 percent and 2.5 percent less than their market prices, respectively. Because he cannot reject price-taking behavior for the remaining fifty smaller firms, he tests to see if the two largest firms jointly maximize profits, according to the dominant firm model. He rejects this hypothesis at the one percent significance level. Roberts thus concludes that to understand the behavior of the top two firms in the industry the empirical framework must include measures of non-price competition.

In a related paper Martin (1988a) uses firm-level quarterly data from four firms in the medical-surgical supplies industry and four firms in the motor vehicle industry over the period 1973-1982 to estimate firm-level price cost margins. He does not calculate conjectural variations directly, but tests only for price taking behavior. A firm does not exercise market power if the difference between price and marginal revenue is not statistically different from zero. He does not test for collusion. He finds that all firms in the sample exercise market power. These results may be suspect, however, because he does not incorporate product differentiation into his model. He also assumes constant returns to scale.[41]

In sum, the voluminous literature analyzing the relationship between market structure and profitability provides few definitive results. Results from research that tries

[41] Because the theoretical specification of Martin's model includes a firm's function coefficient, the model can accommodate both increasing and decreasing returns to scale. The function coefficient is an index of returns to scale. He assumes constant returns to scale, however, to avoid estimation of a production function and subsequent calculation of the function coefficient.

to distinguish between the efficiency and collusion hypotheses by including both market share and measures of market concentration as regressors are inconclusive. Although studies that test for specific kinds of firm behavior do identify non-competitive behavior in certain industries, this literature does not analyze the effect, if any, that firm behavior has on the prices that firms receive. The majority of the manufacturing studies that I review in this section, furthermore, assume product homogeneity, an assumption which is inappropriate for the hospital industry.

This dissertation tries to rectify these shortcomings in an analysis of the relationship between hospital profitability and market structure in Florida hospital markets. I incorporate product differentiation into a profit maximization model and estimate conjectural elasticities for 185 Florida hospitals. In addition to testing for both Cournot behavior and collusion, I also discern the effect that hospital behavior has on price by estimating a price function that includes variables that describe hospital behavior as regressors. Because the model assumes profit maximization, I first consider, in Chapter Two, the appropriateness of this assumption for the hospital industry. Chapter Two concludes with a profit-maximization model that describes the relationship between a hospital's margin and its market share.

IV. Tables

A. Table 1.1

Examples of Estimated Conjectural Elasticities from Inter-industry Studies

Author(s)	Estimated Conjectural Elasticity	t-ratio
Applebaum (1982)		
Industry:		
Rubber	.0186	1.065
Textile	.0368	0.739
Electrical machinery	.2001	3.678
Tobacco	.4019	3.052
Clarke, et al. (1984)		
Industry:		
Shop and Office Fittings	.0390	not available
Printing Ink	.5350	not available
Telegraph and Telephone	.5360	not available
Overall:		
Mean	.2540	not available
Minimum	.0390	not applicable
Maximum	.5360	
Stalhammar (1991)		
Mean	.0450	not available
Minimum	.0001	not applicable
Maximum	.1900	not applicable

Notes: Applebaum (1982) tests if the estimated conjectural elastcities are significantly different from zero. Clarke, *et al*. (1984) do not test the statistical significance of their estimated conjectural elastcities. Stalhammar (1991) finds statistically significant conjectural elastcities on 32 of the 67 industries studied, but he does not provide any estimates for specific industries. He lists only the average estimated conjectural elastcity and the range of the estimates.

CHAPTER TWO

The Profit-Maximization Assumption and the Relationship Between Hospital Price-Cost Margins and Market Share

I. Introduction

The theoretical model I develop at the end of this chapter incorporates the assumption that all hospitals maximize profits, regardless of organizational status. In spite of the similarities between for-profit and non-profit hospitals that I identify here, it is possible that challenges to the appropriateness of non-profit hospital tax exemption may cause such hospitals to deviate from profit maximization to maintain their favorable tax status.[1] In Section II of this chapter I apply a market segmentation model to the hospital industry, to obtain testable hypotheses about the possible responses by non-profit hospitals given a potential challenge to their tax-exempt status. I test these hypotheses in Chapter Six. Section III discusses current trends in the hospital industry as well as results from empirical work that analyzes the effect of different ownership structures on hospital behavior. Section IV looks at the ownership characteristics of the hospitals that I use in this analysis. Because my main conclusion is that price competition among all hospitals has led non-profit hospitals to behave like for-profit hospitals, I develop a profit-maximization model that describes the relationship between a hospital's margin and its market share in Section V. Section VI contains all tables pertinent to the analyses in this chapter.

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[1] See, for example, Eastern Kentucky Welfare Rights Organization v. Schultz, 370 F. Supp. 325 (D.C. 1973) and the other cases that Potter and Longest (1994) cite.

II. Non-profit Hospital Tax Status and the Community Benefit Standard

Because only non-profit hospitals are exempt from various federal and state taxes, it is possible that differences in tax treatment will lead non-profit and for-profit hospitals to behave differently. Indeed, even if non-profit hospitals maximize profits, recent Federal and state challenges to the non-profit hospital tax exemption may cause these hospitals to deviate from profit maximization to retain their advantageous tax status [Eisert (1995)]. I now briefly review non-profit hospital tax exemption laws.

Potter and Longest (1994) summarize the state and federal laws surrounding the non-profit hospital tax exemption.

> The laws of tax exemption applied to nonprofit hospitals are complex, and the interactions among them are often confusing. A typical voluntary hospital is organized as a nonprofit corporation under state law, which excludes it from state income (and other corporate) taxes. Such a hospital is exempt from municipal, county, and special district real estate taxes by meeting a further standard of charitable status, which is defined by state laws separately from nonprofit incorporation law. Finally, the voluntary hospital is exempt from federal income taxes by virtue of both its nonprofit corporate status and its meeting a federal standard of charitability as defined by section 501 (c)(3) of the Internal Revenue Code . . . . [A]s a practical matter, a hospital could lose its charitable exemption from local real estate taxes while remaining fully exempt from state and federal income taxes [p. 394].

I now discuss the conditions for non-profit hospital exemption from federal taxation under section 501(c)(3) of the Internal Revenue Code. Under section 501(c)(3) of the Internal Revenue Code, an organization must be "operated for religious, charitable, scientific testing for public safety, literacy, or educational purposes." Hospitals commonly qualify for exemption under the "charitable" clause.

Prior to 1969 the Internal Revenue Service (IRS) ruled that a hospital could obtain an exemption only if it "operated to the extent of its financial ability for those not

able to pay for the services rendered and not exclusively for those who are able and expected to pay" [Fox and Schaffer (1991) at 252]. In 1969 the IRS expanded its definition of "charitable" to conform with the Department of the Treasury's definition and the common law interpretation of the term. American common law,

> as summarized in the Restatement of the Law of Trusts 2d, defines a charitable trust as "a fiduciary relationship with respect to property . . . subjecting the person by whom the property is held to equitable duties to deal with the property for a charitable purpose (American Law Institute 1959: 210)." The trustee can be a corporation as well as an individual. The concept of "community benefit" is integral to a charitable trust in the sense that its benefits must be given to the community or an indefinite group of persons, not to any particular individuals or group. In particular, the promotion of health is deemed to be "of such social interest to the community as to fall within the concept of charity" (American Law Institute 1959: 248). [Potter and Longest (1994) at 396-97)].

Rather than focus solely on the provision of free care, the courts and the IRS now consider operation of an emergency room open to everyone without regard to ability to pay [Fox and Schaffer (1991)][2] and the amount of under-reimbursed care that a non-profit hospital provides to be the two most important factors in determining if a hospital meets the community benefit standard [Eisert (1995), Fox and Schaffer (1991)].[3]

In sum, even if non-profit hospitals do maximize profits, they also must satisfy the community benefit standard to maintain their federal tax exempt status. The courts'

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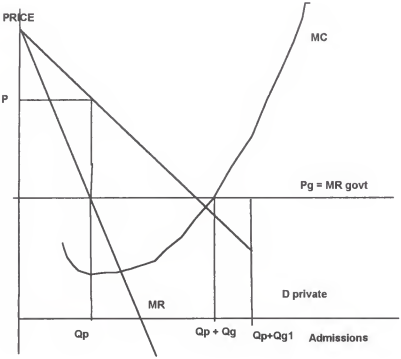
[2] Under the Consolidated Omnibus Budget Reconciliation Act of 1985 (COBRA), hospitals participating in Medicare must provide emergency room care for patients unable to pay. See Fox and Schaffer (1991) at footnote 7.

[3] Other factors include : 1. The presence of civic leaders rather than hospital administrators and physicians on the governing board; 2. provision of staff privileges to all qualified physicians in area; and 3. corporate separateness of the hospital if it is part of a multi-entity system. See Eisert (1995), p. 1, footnote 2.

interpretation[4] of the community benefit standard thus may act as a constraint and cause non-profit hospitals to deviate from profit maximization. Using a segmented markets model, Figure 2.1 illustrates that even if both non-profit and for-profit hospitals maximize profit, they will act differently if the courts strictly enforce the community benefit standard.

Figure 2.1. A Segmented Markets Model



The oligopolistic hospital faces a downward sloping demand curve for privately insured patients, $D_{private}$. The corresponding demand curve for government insured

[4] See Eastern Kentucky Welfare Rights Organization v. Simon, 506 F.2d 1278, 1287-89 (D.C. Cir. 1974), vacated, 426 U.S. 26 (1976) and other cases and IRS rulings that Potter and Longest (1994) cite.

patients (Medicare and Medicaid), $p_g = MR_{govt}$, is horizontal because the hospital acts as a price taker for these patients. In this segmented market the hospital will serve Q_p privately insured patients at price p and accept government insured patients, Q_g, until the government reimbursement rate equals marginal cost. Hospitals treat a total quantity, therefore, of $Q_p + Q_g$ patients.

Figure 2.1 illustrates that both non-profit and for profit hospitals will accept government insured patients when the marginal revenue from treating these patients exceeds the marginal revenue earned from treating privately insured patients.[5] If compliance with the community benefit standard causes departure from profit maximization, however, non-profit hospitals will treat additional government insured patients, serving, for example, $Q_p + Q_{g1}$ patients, which exceeds the profit maximizing quantity of $Q_p + Q_g$.[6] At the quantity $Q_p + Q_{g1}$ non-profit hospital margins decrease because the marginal cost of treating these patients exceeds MR_{govt}. At quantities up to $Q_p + Q_g$, treatment of additional government insured patients increases margins because $MR_{govt} > MC$.

Including interaction variables that combine non-profit and for-profit dummy variables with the percentage of Medicare and Medicaid patients that the hospital treats in a net margin equation tests if compliance with the community benefit standard alters non-profit hospital behavior. If the constraint alters non-profit hospital behavior, the hospital

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[5] The total number of government patients whom the hospital treats is the difference between Q_p and $Q_p + Q_g$.

[6] The quantity, Q_{g1}, may reflect charitable giving, for example, consistent with a non-profit hospital's corporate mission.

will accept $Q_p + Q_{g1}$ patients, which will have a negative effect on margins. The sum of the coefficients on the non-profit interaction variable and the percentage of Medicare and Medicaid patients variable therefore will be negative.[7] If the community benefit standard does not cause non-profit hospitals to deviate from profit maximization, this sum will be positive for both for-profit and non-profit hospitals. In this case both for-profit and non-profit hospitals will accept $Q_p + Q_g$ patients. I now discuss recent changes in the hospital industry that have caused non-profit hospitals to adopt for-profit hospital behavior.

III. Factors Contributing to the Growing Similarity Between Non-Profit and For-Profit Hospitals

This section argues that the changing structure of the hospital industry, arising primarily from third party payors' cost containment initiatives, is reducing the differences between for-profit and non-profit behavior. Before examining this evidence I emphasize two preliminary arguments. First, non-profit status does not preclude a hospital from earning a profit. Non-profit status only prohibits the distribution of profits to owners [Hansmann (1980)]. Second, because hospitals were originally true charitable organizations, "historical factors probably play a large role in explaining why hospitals are typically non-profit" *[Ibid.* at 73].[8]

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[7] In such a regression government hospitals will be the omitted category. The total effect that Medicare and Medicaid patients have on non-profit hospital margins will be the sum of the coefficients on the non-profit interaction variable and the percentage of government insured patients variable.

[8] See also Gray (1991) at 61-65.

In general third-party payors, by instituting such practices as case rates, capitation, increased utilization review, and precertification programs, are primarily responsible for the increased similarity between for-profit and non-profit hospital decision-making. These practices represent a dramatic change from the charge-based reimbursement systems that they replace.

Gray (1991) identifies several additional factors that indicate a growing similarity between non-profit and for-profit hospitals. First, charitable contributions no longer are the primary revenue source for non-profit hospitals. These hospitals are increasingly dependent on patient service revenues because charitable contributions have not kept pace with the increasing cost of providing care. Declining charitable contributions have also resulted in the non-profit hospital's increased reliance on debt financing. Institutional investors are the principal holders of this debt. Non-profit hospitals, therefore, have become accountable to lenders. This accountability provides an incentive to act efficiently and secure financing at favorable rates.

Second, management contracts, involving either the entire hospital or an individual department, also have become more prevalent in the hospital industry. A proprietary management firm may either manage an entire non-profit hospital or control several clinical departments, such as the emergency room. These contracts offer the hospital access to sophisticated accounting systems, personnel, and marketing and advertising resources. In addition, hospitals have begun forming alliances that are "for-profit organizations that operate and are taxed as cooperatives" [Gray (1991) at 83]. These alliances imitate for-profit systems by issuing equity capital as a source of

financing. The increased use of management contracts and the growth of such alliances have further increased the economic similarity between non-profit and for-profit hospitals.

Increased price competition among hospitals, as well as the trends just described, to a certain degree, have invalidated the early economic models of hospital behavior based on utility maximization and physician control. Section A describes these models briefly, and Section B discusses empirical literature finding similarities between non-profit and for-profit hospitals.

A. Early Models of Hospital Behavior

Newhouse's (1970) model of hospital behavior assumes that hospital administrators, trustees, and medical staff manage the hospital so as to maximize their utility. He assumes that their utility functions depend on both the quality and quantity of services provided. Pauly and Redisch (1973) base their model of hospital behavior on the assumption that the physician has de facto control over hospital operations. These authors conclude that non-profit status may lead to inefficient resource allocation because non-profit hospitals will provide too many services and, possibly, an inefficiently high level of quality.

These models no longer reflect the distribution of hospital decision making power because third-party payors are increasingly acting as hospital and physician monitors.[9]

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[9] Even prior to the widespread use of managed care, researchers observed that insurers are natural monitors of medical services:

> Since, in fact, many consumers band together by choice or circumstance into groups covered by health insurance, it would seem that the job of evaluating the quality and value of medical services and relating them to price would fall upon the insurers. . . . To the extent that the

Hospitals no longer can afford to maximize the quantity of services that they offer to patients because of the trend toward capitation and utilization review by private payors. Similarly, precertification requirements reduce the physician's autonomy [Gray (1991), Chp. 11]. In addition to precertification of hospital admissions, many payors conduct daily review processes designed to evaluate the appropriateness of continued hospitalization [*Ibid.*].

The earlier models of hospital behavior based on either physician or administrator utility maximization, furthermore, allow for the possibility that non-profit hospitals shift the costs of providing under-reimbursed care for government-insured patients to privately insured patients. By definition, a hospital engages in cost-shifting if it increases the price it charges to privately insured patients in response to a reduction in government reimbursement for treatment of Medicare and Medicaid patients [Morrisey (1994), Dranove (1988)]. Because cost-shifting requires that the hospital currently charges less than the profit maximizing price to private pay patients, it is impossible for a profit maximizing hospital to shift costs in this manner [Morrisey (1994), Dranove (1988), Hoerger (1991), Pauly (1988)]. Successful cost-shifting, furthermore, requires price insensitive purchasers. Increased price competition, therefore, reduces the ability of non-profit hospitals to shift costs and it should align the behavior of non-profit and for-profit hospitals.[10] Indeed, Dranove (1988 at 56) states:

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insurer defers to the physician's "discretion" and "judgment" he forgoes the role of monitor" [Clark (1980) at 1421].

[10] Some researchers conclude, however, that non-profit hospitals can still cost-shift. Hoerger (1991), using a national panel data set covering the period 1983-1988, analyzes the effect that the implementation of the Medicare prospective payment system had on hospital profitability. He finds that

> The recent growth of Health Maintenance Organizations and Preferred Provider Organizations, however, suggests that those who pay for hospital services are becoming aggressive price shoppers. . . . As these trends continue, the space of pricing strategies to at least break even must shrink. Hospitals will move closer to profit-maximizing prices, and cost shifting will likely disappear.

B. Empirical Evidence

Non-profit hospitals may be less efficient than are their for-profit counterparts because there is no residual claimant to monitor their behavior. They may also provide more charity care than do for-profit hospitals, because their legal status implies a duty to serve their community. Becker and Sloan (1985) and Herzlinger and Krasker (1987) refute these hypotheses empirically.

Becker and Sloan (1985), using 1979 data from the American Hospital Association, and controlling for such factors as size, geographic location, and payor mix, eliminate most of the cost differential stemming from ownership status. They find no difference in profitability, furthermore, between non-profit and for-profit hospitals. In addition, Herzlinger and Krasker (1987) use data from 1977-1981 to analyze fourteen hospital chains (725 hospitals). They find that non-profit hospitals do not provide more indigent care than do their for-profit counterparts. They also observe that there is no difference in patient revenues between the two groups.[11]

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in response to this regulatory change, for-profit hospitals have greater variability in their profits than do non-profit hospitals. He concludes that this result is evidence that non-profit hospitals do not maximize profits but that they can adjust elements in their utility function, subject to a profit constraint- that is, cost shift- in response to a regulatory change. There are other requirements for cost shifting to be possible, however, as I discuss in the text.

[11] Gray (1991) at 367-368, footnote 14 cites references that criticize this article for making conclusions that the data do not support. These criticisms, in general, concern the quality of the data. Herzlinger and Krasker, for example, include Kaiser HMO hospitals in their non-profit sample.

In a more recent analysis, Eisert (1995) uses 1991 data from the AHA American Hospital Annual Survey of Hospitals and the Health Care Financing Administration's 1991 Medicare Minimum Cost Report, covering approximately 6,800 hospitals, to find out if the number of Medicaid patients treated differs between for-profit and non-profit hospitals. She observes that non-profit hospitals do treat more Medicaid patients than do for-profit hospitals and interprets this result as evidence that non-profit hospitals do provide more service to the community at large than do for-profit hospitals. But she also discovers that as the number of for-profit hospitals in an area increases, non-profit hospitals treat fewer Medicaid patients. This result indicates that the presence of for-profit hospitals in a market increases the similarities between the two kinds of hospitals.

IV. Organizational Characteristics and Behavior of Florida Hospitals

This section argues that the data that this dissertation uses supports the profit maximization assumption underlying the theoretical model that Section V presents. Table 2.1[12] illustrates the ownership characteristics of Florida hospitals for the years 1990 and 1992.[13] Table 2.1 shows that, in both 1990 and 1992, approximately 43 percent (92) of all of the short-term general hospitals, which are the focus of this research, are for-profit firms. The large number of for-profit hospitals surely will affect the strategies of the non-profit hospitals. When all hospitals in an area face the same competitive environment,

[12] Section VI contains all tables pertinent to the analysis in this chapter.

[13] As Chapter Four discusses in depth, I obtain this ownership data from the Florida Agency for Healthcare Administration, which mandates that all Florida hospitals report annual financial data.

regulatory mandates, and accreditation requirements, they are likely to behave in a similar fashion, regardless of their organizational status [Gray (1991 at 91)].

Sloan and Vraciu (1983), furthermore, in a study comparing Florida non-profit hospitals with both independent and chain proprietary hospitals, find

> a clear pattern of similarities between non-teaching not-for-profit and investor-owned hospitals in Florida. Our comparison of relative community costs of the two types of institutions reveal[s] no real differences. Investor-owned system hospitals and not-for-profit hospitals are virtually identical in terms of after-tax profit margins, percentages of Medicare and Medicaid patient days, and the dollar value of charity care and bad debt adjustments to revenue [p.34].[14,15]

In sum, analysis of the data that I use in this research and evidence from other studies on Florida hospitals indicate that the use of a profit maximization assumption to model hospital behavior is appropriate. Changes in hospital reimbursement methods further support use of such a model. As Chapter Six details, moreover, I also find that the Federal courts' interpretation of the community benefit standard does not cause Florida non-profit hospitals to depart from profit-maximizing behavior. The conclusions that I reach in this chapter, therefore, support the use of a profit maximization assumption to model hospital behavior.

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[14] The authors adjust the hospital accounting data to try to account for the tax treatment of the two organizational forms. For example, they classify contractual allowances for Medicare and Medicaid patients as "taxes" that all hospitals paid. To improve the accuracy of their comparative analysis they also deduct income taxes from for-profit hospital revenue. They make this deduction because patients presumably benefit from the taxes that for-profit hospitals pay . They consider hospital revenue to be the "cost" that the hospital imposes on the community.

[15] Gray (1991) at 367, footnote 12, criticizes this study because it includes only short-term general hospitals with fewer than 400 beds. This omission has the effect of narrowing the cost differentials between the varieties of ownership.

V. A Profit-Maximization Model

I now analyze the relationship between a hospital's price-cost margin and its market share. The model, based on oligopoly theory, distinguishes empirically between the differential efficiency and collusion hypotheses for hospitals providing differentiated services.[16] The analysis uses market share, rather than the Herfindahl index, as the market structure variable in the net margin equation. The use of market share distinguishes this study from earlier empirical work on hospital profitability and market concentration [Dranove, *et al.* (1993), Melnick, *et al.* (1992)], which include only the Herfindahl index as the market structure variable. This model illustrates that for firm or hospital level data, market share, rather than the Herfindahl index, is the theoretically correct measure of market structure. The Herfindahl index, by contrast, is appropriate to use when the data are aggregated to the market or industry level. Recall that the original studies of the relationship between margin and concentration use industry-level data. In such an analysis the estimated coefficient on the Herfindahl index captures both firm-specific and market effects [Martin (1993), Ch. 16]. It is the presence of firm-specific effects that provides the basis for Demsetz's argument concerning large market share firm efficiency. Here, I concentrate on the importance of hospital-specific effects.[17]

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[16] The model that I develop in this section is based on the model by Clarke and Davies (1982), which builds on the work of Cowling and Waterson (1976). This model, however, incorporates product differentiation in a manner that Geroski (1983) suggests.

[17] One study on hospital competition does acknowledge that both firm and market level effects may exist. Dranove, *et al.* (1993) attempt to distinguish between the collusive market power and differential efficiency hypotheses by including both market share and the Herfindahl index as independent variables in their net margin equation. They argue that if efficiency best explains the relationship between the Herfindahl index and hospital profitability, including market share as a regressor will reduce the significance of the Herfindahl index. They find that the coefficient on the Herfindahl becomes smaller but remains significant when both market share and the Herfindahl index appear in the net margin

The consumer good of interest is the product "insured medical care." Following Pauly (1988), I consider the insurer or third party payor to be the "manufacturer" of this product:

> The insured may have some choice as to which of the many possible providers to use, but the final result is as if the insurer bought the medical services (as inputs) . . . and then in effect resold this package to the insured patient in return for the insurance premium. It is as if doctors, hospitals, or other providers are "upstream" producers of inputs which are combined with insurance to produce a final product (p.113).

The hospital, therefore, supplies an input to the insurer. Assume that each hospital first makes an output decision and then competes partly on price for inclusion in managed care networks. The assumption that the firms make collusive decisions on output rather than price makes this model extremely applicable to the hospital market because:

> [t]he complexity of a [hospital's] product makes it difficult for price collusion to be successful. Collusion regarding visible technology and equipment might be expected to be significantly easier to maintain than collusion regarding prices of services. In fact, most known [hospital] collusions focus on easily observable output features or specific services such as maternity care [Woolley and Frech (1988-89 at 63)].

I now present a model, widely accepted in the empirical industrial organization literature, to illustrate the determinants of the relationship between a hospital's price-cost margins and its market share. Let there be N hospitals operating in N hospital-specific geographic markets. As Chapter Four explains, I use patient discharge data to define the

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equation. The authors conclude that this relationship provides evidence against the differential efficiency hypothesis. Shepherd (1972), Gale and Branch (1982), and Ravenscraft (1983), all conduct similar analyses using manufacturing data, as Chapter One, Section III discusses. Geroski (1982), however, argues that models including both market share and measures of concentration as independent variables are misspecified.

hospital's geographic market. Each hospital produces a differentiated basket of inpatient services. Hospital i's profit is:

$$\pi_i = p_i q_i - c_i(q_i) - F_i, \tag{2.1}$$

where q_i is the quantity of services that hospital i provides, p_i is the corresponding net price[18] the hospital receives, c_i is variable cost, and F_i is total fixed cost. Net price is a function of all quantities in hospital i's market, $p_i = f(Q_i)$ (the inverse demand function), with $Q_i = q_i + Q_{-i}$, where Q_i is the total quantity of services that all hospitals in hospital i's market supply and Q_{-i} is the quantity that the hospitals in i's market, except for hospital i, provide. Assume, furthermore, that marginal costs are constant and equal to average variable cost and that there are "long-lived efficiency differences among firms so that $c_1 \leq c_2 \leq \ldots c_N$, with at least one inequality strict" [Schmalensee (1987 at 399-400)].

I incorporate product differentiation spatially[19] using the parameter θ, ($0 \leq \theta \leq 1$). Rewrite $Q_i = q_i + Q_{-i}$, as $Q_i = q_i + \theta Q_{-i}$, [Geroski (1983)], so that Q_i now represents a hospital's effective market. If $\theta = 1$, then all hospital services in the market are perfectly substitutable, and if $\theta = 0$, then each hospital is a monopoly.

To represent more accurately a hospital's "effective" market, I define hospital geographic markets using patient origin data, rather than artificial boundaries. Using arbitrary borders such as political boundaries or fixed distances to define geographic

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[18] I define net price as charges less contractual allowances because charges do not accurately reflect the hospital's actual reimbursement. Noether (1988) finds no significant relationship between Medicare charges and concentration. Similarly, Dranove, *et al.* (1993) find the Herfindahl index, in a regression of gross margin on hospital characteristics such as size and patient mix, to be insignificant.

[19] When products are spatially differentiated, all products may not be substitutes. Each consumer prefers a product with certain characteristics, one of which may be the geographical location of the seller.

where $e_{Qi,Pi} = -\frac{\partial Q_i}{\partial p_i} \cdot \frac{p_i}{Q_i}$ is hospital i's price elasticity of demand, and $S_i = q_i/Q_i$ is hospital i's market share.

Multiplying by (Q_{-i}/Q_{-i}) and simplifying, equation (2.6) becomes:

$$\frac{p_i - MC_i}{p_i} = \frac{[a_i + S_i(1 - a_i)]}{e_{Qi,\,pi}} \,. \tag{2.7}$$

The term on the left hand side of equation (2.7) is the Lerner Index, a measure of the degree of market power; MC_i is the marginal cost to hospital i of providing a basket of inpatient services;[20] p_i is the net price hospital i receives for providing these services; S_i is hospital i's effective market share; $e_{Qi,\,pi}$ is the price elasticity of demand for the services hospital i offers; and α_i is hospital i's conjectural elasticity. Equation (2.7) represents a steady state relationship assuming that the hospital already has made a capacity decision.

The conjectural elasticity is a parameter that reflects hospital conduct. Define hospital i's conjectural elasticity as

$$\alpha_i = (dQ_{-i}/dq_i)(q_i/Q_{-i}) \text{ for all i.} \qquad (0 \leq \alpha_i \leq 1) \qquad (2.8)^{21}$$

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[20] Pautler and Vita (1994) support the use of a market basket of services to analyze the relationship between hospital price-cost margins and market structure because many hospital services are complementary and therefore one should not analyze them in isolation. Data limitations also dictate that a basket of hospital services, not individual hospital services, be the focus of this analysis, because the data do not identify the service-specific contractual allowances necessary to calculate the net margin for an individual service. I cannot calculate service-specific net margins because the data identify contractual allowances only by broad payor category rather than by service category. Net margin is more meaningful for profitability analysis than is gross margin, because gross charges do not accurately reflect hospital reimbursement.

[21] [Clarke, *et al.* (1984) and Clarke and Davies (1982).]

Intuitively, hospital i's conjectural elasticity is its best guess about how the remaining hospitals in the market will respond to changes in its own service production. So, for example, $\alpha_i = 1$ means that, if hospital i increases its output by one percent, it expects its competitors to exactly match this increase. Chapter Three illustrates that results from significance tests on the estimated values of α_i distinguish between the collusive market power hypothesis and the differential efficiency hypothesis.

Rearranging equation (2.8) I obtain the conjectural derivative:

$$dQ_{-i}/dq_i = \alpha_i(Q_{-i}/q_i). \tag{2.9}$$

From equation (2.9) it is clear that α_i represents "the degree of implicit collusion, being the proportionate extent to which each firm believes each other firm will react to its output changes" [Clarke, *et al.* (1984 at 439]. Interpreting α_i within the context of equation (2.7), furthermore,

> [i]t is useful to think of the numerator on the right [of equation (2.7)] . . . as a weighted average of 1 (the monopoly market share) and s_i, the firm market share. An increase in the conjectural elasticity, α_i, increases the weight given to 1, reduces the weight given to s_i, and increases the Lerner index" [Martin (1990) at 77)].

If α_i=0, hospital i believes that other hospitals do not respond to its output choice. If all hospitals in i's market hold these beliefs, a Cournot equilibrium results and $\partial Q_{-i} / \partial q_i = 0$. Using equation (2.7) we find that there will be a positive relationship between hospital i's market share and its price-cost margin. The more efficient[22] hospitals will have higher margins and, because of their efficiency, they will acquire large

[22] Recall that I interpret efficiency broadly. It may reflect cost savings arising from scale economies or product innovation. See the discussion in Chapter One, Section III.

market shares, thereby increasing the level of concentration in the market. A positive relationship between market share and net margin, therefore, is consistent with the differential efficiency hypothesis. Under this hypothesis firm performance determines market structure. "[L]ower values of α imply that firm [hospital] i believes that there is some scope for improving its market share; i.e., that rivals will not react [adjust output] by as much proportionately" [Clarke and Davies (1982 at 279)]. Low values of α that are not significantly different from zero, therefore, identify efficient providers not engaging in implicit collusion.

Finding evidence of a Cournot equilibrium, however, does not imply that hospitals are price-takers.[23] Although an α_i not significantly different from zero implies that hospitals are not colluding, they nonetheless possess hospital-specific market power. Market share can be positively related to hospital margin for four reasons.[24] First, a high market share hospital may have dominant firm market power, which can raise prices for all hospitals in the market. Second, large market share hospitals may earn a premium for providing higher quality services than do other hospitals in its market. Third, large market share hospitals may be superior innovators. Fourth, large market share hospitals may have lower costs arising from scale economies. Estimating market share interaction terms can help to distinguish empirically among these various causes of hospital-specific

[23] A conjectural derivative equal to -1 implies perfect competition [Bresnahan (1989)]. Although the model presented here rules out price-taking behavior by defining the conjectural elasticity to be between zero and one following Clarke, *et al.* (1984), I test the null hypothesis that a hospital's estimated conjectural elasticity is equal to negative one in Chapter Five. I expect to reject the null hypothesis because of the oligopolistic nature of hospital markets [Noether (1988)].

[24] Ravenscraft (1983) invokes these same arguments in his analysis of profitability using the Federal Trade Commission's Line of Business data.

market power.[25] Interacting market share with a variable indicating the availability of "high-tech" services isolates the return to large market share hospitals from superior innovation. In a similar manner, interacting market share with a capital intensity variable helps to inform us if larger market share hospitals have higher margins arising from scale economies.

Notice that unless there are measures of quality for the hospital, the effects of dominant firm market power and a quality premium are indistinguishable empirically and the market share coefficient will reflect the presence of both of them. Ravenscraft states (1983 at 23):

> It is important to realize that market share should measure market power stemming from product differentiation, since it captures advantages unique to the [hospital]. Market share does not measure dominant firm market power, which raises prices and profits for all [hospitals] in the industry. Dominant firm market power can be measured by a dummy variable equal to one for [a hospital] in a [market] having a large leading [hospital] with no close rivals.

If $\alpha_i > 0$, firms expect that competitors will match their output decisions to some degree [Bresnahan (1989) at 1028]. An estimate of the conjectural derivative, and hence the conjectural elasticity, reveals "how close to a completely collusive outcome the [firm's] expectations induce" [*Ibid.* at 1029]. For $0<\alpha_i<1$, a positive relationship between market share and profitability exists, although this relationship is weaker for larger values of α_i [Clarke, *et al.* (1984)]. A finding that $\alpha_i > 0$ implies cooperative behavior; and such a finding is consistent with the hypothesis that market concentration leads to collusion and therefore, high profits.

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[25] If the market share interaction terms are significant, their presence will reduce the significance of the market share coefficient [Ravenscraft (1983)].

The limiting case is α_i=1, reflecting perfect coordination on output decisions among hospitals. In such a case hospital i expects that its rivals will exactly match any percentage change in its output. For example, from equation (2.9) we find that if α_i=1, hospital i expects that if it reduces its output, then hospital j will also reduce its output, such that Q_{-i}/q_i remains constant. Equation (2.7) illustrates that when α_i = 1 each hospital's price-cost margin will be independent of its market share.

It is important to realize, however, that other hospital behavior, in addition to collusion to restrict output below the competitive level, may result in a conjectural elasticity equal to one. Hospitals may enter into joint ventures and agree to share certain costly, sophisticated services, for example, whereby each hospital is the sole provider of a certain service, assuring each hospital a monopoly position. Alternatively, hospitals may engage in cooperative planning or enter into a system affiliation. Under these various scenarios hospital margin also will be independent of market share.[26]

In sum, the use of market share rather than the Herfindahl index in an analysis of hospital net margin is theoretically appropriate. Estimation of the conjectural elasticity and a test of its statistical significance, furthermore, can help to differentiate between the efficiency and collusion interpretations of a positive relationship between market structure and hospital margin that previous studies of hospital competition identify. Chapter Three

[26] It is important to realize that estimation of a hospital's conjectural elasticity cannot measure price collusion. Fee information that hospitals provide to both insurers and to the general public, for example, may facilitate hospital price fixing. This analysis cannot capture the magnitude or the existence of such a strategy

discusses the empirical specification of equation (2.7) as well as the significance tests for the estimated conjectural elasticities.

VI. Tables

A. Table 2.1

Hospital Ownership Characteristics

Hospital Ownership Characteristics	**1990**	**1992**
All Hospitals		
For-profit	151 (49.8 %)	151 (50.2%)
Non-profit	110 (36.3 %)	115 (38.2%)
Government	42 (13.9 %)	35 (11.6%)
Total	303 (100 %)	301 (100 %)
S-T General Hospitals		
For-profit	92 (43.2%)	92 (44.0%)
Non-profit	88 (41.3%)	90 (43.1%)
Government	33 (15.5%)	27 (12.9%)
Total	213 (100 %)	209 (100 %)

Notes: I obtain this ownership information from the financial data that Florida hospitals submit annually to the Florida Agency for Healthcare Administration.

CHAPTER THREE

Empirical Specification of the Model

I. Introduction

This chapter discusses the link between the theoretical model that Chapter Two develops and the empirical model that Chapter Five estimates. The discussion also involves exploring measurement issues introduced when one substitutes average variable cost for marginal cost and uses an accounting rather than an economic valuation of capital. This chapter concludes with the empirical specification of equation (2.7) and a discussion of the significance tests for the estimated conjectural elasticities.

II. Derivation of the Empirical Model

Estimation of equation (2.7) using accounting data requires the substitution of average total cost for marginal cost. Without specifying a functional form for the underlying production function, the relationship between marginal cost and average total cost is:

$$MC \equiv AC + q\frac{\partial\ AC}{\partial\ q}.\ ^{1} \tag{3.1}$$

According to equation (3.1), marginal cost differs from average total cost by an adjustment factor representing the per unit effect of increased output on average total costs, multiplied by total output.

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[1] Equation (3.1) assumes that MC and AC are functions of input prices and output. In other words, for example, marginal cost is the first derivative of the indirect cost function $C = \Sigma_i\ [w_i\ x_i^*(w_i,\ q^0)]$, where the x_i^* represent the values of the factors of production that minimize cost of producing q^0, a parametric value of output.

Substituting equation (3.1) into equation (2.7) and rearranging terms yields,

$$\frac{p_i - AC_i}{p_i} = \frac{[a_i + S_i(1 - a_{ii})]}{e_{Q_i p_i}} + \left[\frac{q_i\left(\frac{\partial AC_i}{\partial q_i}\right)}{p_i}\right]. \tag{3.2}$$

We can express average total cost as a function of both fixed and variable components,

$$AC = (wL + \lambda p^k K)/q\,, \tag{3.3}$$

where L represents a vector of variable factors, w is a vector of factor prices, $p^k K$, is the value of a hospital's assets, and λ is the annual opportunity cost of capital. Substituting equation (3.3) into equation (3.2), we arrive at:

$$\frac{p_i - AVC}{p_i} = \frac{[a_i + S_i(1 - a_i)]}{e_{Q_i p_i}} + \left[\frac{q_i\left(\frac{\partial AC_i}{\partial q_i}\right)}{p_i}\right] + \frac{\lambda p^k K_i}{p_i q_i}\,, \tag{3.4}$$

where the term on the left-hand side of equation (3.4) is the margin of price over average variable cost, with $AVC = (wL_i)/q_i$.[2]

Estimation of equation (3.4) requires measurement of the divergence, if any, between marginal and average total cost (the second term on the right hand side of equation (3.4)) and of the economic valuation of capital (the numerator of the third term on the right hand side of equation (3.4)). Section III discusses these measurement issues.

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[2] Inter-industry studies of profitability commonly use price over average variable cost as a dependent variable. See, for example, Domowitz, Hubbard, and Petersen (1986).

III. Measurement Issues

A. The Substitution of Average Cost for Marginal Cost

The substitution of average for marginal cost is theoretically correct only under the assumptions of either constant returns to scale or operation at efficient capacity. Violating these assumptions can introduce measurement error into the price-cost margin equation. Recall from Section II that estimation of equation (3.4) requires measurement of the divergence, if any, between marginal and average total cost (the second term on the right hand side of equation (3.4)). I now discuss the expected sign of this term as well as available proxies that adequately represent the divergence between average and marginal cost.

While average total cost will equal marginal cost under the assumption of constant returns to scale, Harris (1988) argues that marginal cost can differ among firms even under constant cost conditions. Marginal cost can still differ among hospitals, therefore, even if returns to scale are constant. In this scenario a firm that is a successful innovator will have an absolute cost advantage and earn an efficiency rent that can persist until the next drastic technological change.

If returns to scale are not constant, the sign of the bracketed term in equation (3.4) depends on the sign of the derivative, $\frac{\partial AC_i}{\partial q_i}$. Express this derivative as

$$\left(\frac{\partial\, AC_i}{\partial\, q_i}\right) = \frac{MC_i}{q_i} - \frac{AC_i}{q_i} \tag{3.5}$$

From equation (3.5) we note that if there are increasing returns to scale, then average cost is greater than marginal cost, the derivative is negative, and equation (3.4)

understates margins by substituting average for marginal cost. In the case of decreasing returns to scale, marginal cost exceeds average cost, the derivative is positive, and equation (3.4) overstates margins.

Without knowledge of the nature of the returns to scale, the sign of the derivative is indeterminate. In their study on hospital costs, Freidman and Pauly (1982) conclude that long run marginal costs are approximately 98 percent of long run average costs.[3] Their finding implies that returns to scale are nearly constant. Their data, however, are from the late 1970s, before the era of managed care and reduced utilization.

Reduced hospital inpatient utilization has created excess capacity (unused beds) in the market. The Florida hospitals in the sample, for example, have an average occupancy rate of only approximately 52 percent. The presence of excess capacity implies that marginal costs will be fairly constant [Dranove (1988)] and substantially less than average costs [Dranove, *et al.* (1986)]. The sign of the derivative in equation (3.5), therefore, is most likely negative. It is important to realize that this excess capacity is an artifact of a cost-based reimbursement system. The relationship between marginal and average cost in Florida hospitals may change as the market works to reduce excess capacity.

Martin (1984) advocates using proxy variables to control for the differences between average and marginal cost. I use the availability of technologically advanced services and the hospital occupancy rate as proxies to represent any divergence between

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[3] The authors actually find that "anticipated" marginal costs are 98 percent of long run average total costs. Dranove (1988) summarizes, "Anticipated costs are those incurred over the medium and long-run planning horizons. If hospitals base their prices on the same planning horizon, then they base their prices on anticipated costs. The conclusion is that the marginal costs relevant to pricing decisions roughly equal average total costs" (p. 50, footnote 4).

average and marginal cost. The greater is the number of technologically advanced services, which are capital intensive, the greater is the divergence between average and marginal cost. Similarly, the lower is the occupancy rate, the greater is the divergence between average and marginal cost.

For this analysis I assume that any measurement error associated with the proxy variables is independent of both the estimated residual and other independent variables in equation (3.4). Under these conditions, evaluated on the criterion of asymptotic bias, use of a poor proxy is preferable to omitting the unobservable independent variable from the regression equation [McCallum (1972), Wickens (1972)].

B. The Economic Versus the Accounting Valuation of Capital

Differences between the accounting and economic valuations of capital will also affect estimation of equation (3.4) because the ratio of capital to sales is an independent variable in this equation. The numerator of the third term on the right hand side of equation (3.4) therefore, should reflect the economic valuation of capital.

It is necessary to use the ratio of capital to sales as an independent variable because the dependent variable in equation (3.4) does not include a cost of capital component. From a practical point of view, this omission occurs because accounting data does not reveal the risk-adjusted cost of capital.[4] Including the ratio of capital to sales as an independent variable in equation (3.4) corrects for this deficiency and converts the accounting price-cost margin to the economic price-cost margin. Implicit in this

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[4] Benston (1982) provides many detailed examples of other balance sheet items that do not accurately reflect economic value.

adjustment is the assumption that both the opportunity cost of capital and the depreciation schedule are identical for all hospitals in the sample [Schmalensee (1989)].[5] Such an adjustment is theoretically correct, however, only when the estimated coefficient on the capital intensity term, λ, equals the risk adjusted cost of capital [Fisher (1987), Liebowitz (1987)]. Such an equality will occur only when a firm uses the Hotelling valuation for capital assets. The resulting depreciation schedule "implies a valuation of capital ("Hotelling valuation") at the present value of the associated remaining net revenue stream using the firm's risk-adjusted discount rate" [Fisher (1987) at 385]. This depreciation schedule depends on future revenue rather than cost.

Fisher (1987) argues that capital measurement errors are likely to be correlated with other independent variables in a regression equation explaining firm profitability. If there is such a correlation, the coefficient on the capital intensity term in equation (3.4) will be asymptotically biased.[6] Long and Ravenscraft (1984) show, however, that even if differences between economic and accounting depreciation are important, such that the coefficient on the capital intensity term is asymptotically biased, these differences do not distort the concentration-profitability relationship, which is the focal point of my analysis.

Both Martin (1984), and Long and Ravenscraft (1984), furthermore, justify the inclusion of the capital intensity term in equation (3.4) on additional grounds. First, the

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[5] All hospitals in my sample use the same depreciation method. The Florida Agency for Healthcare Administration mandates that for reporting purposes all hospitals use straight-line depreciation.

[6] Benston (1982, 1985) argues, more generally, that because accounting data cannot accurately represent economic profitability, any positive relationship between concentration and industry profits reflect only spurious correlation. Other economists [Martin (1984), Ravenscraft and Long (1984), and Ravenscraft (1982), for example], however, take the opposite position.

firm's profit maximization problem mandates the inclusion of a capital intensity term in equation (3.4).[7] Second, the accounting price-cost margin is an adequate proxy for the Lerner index, even if returns to scale are not constant, if one takes into account the cost elasticity of the average cost curve, which represents the difference between marginal and average cost. As I discuss in Section III A, equation (3.4) does include variables that stand as proxies for the divergence between marginal and average cost. Third, and perhaps most important, Long and Ravenscraft (1984) argue that accounting data must reflect economic value, to some degree, because stock prices respond to accounting profit announcements. I now present the empirical specification of equation (3.4).

IV. Regression Model

Equation (3.6) is the specification of a fixed effects model I use to estimate equation (3.4).

$$Margin_{i,t} = \beta_{0,i} + \beta_{1,i}S_{i,t} + \beta_2\left(\frac{p^k K_i}{p_i q_i}\right)_t + \underline{\beta}\, Z_{i,t} + u_{i,t}\ , \tag{3.6}$$

where $Margin_{i,t}$ which is hospital i's price-average variable cost margin in year t, equals $\frac{p_i - AVC_i}{p_i}$, $\beta_{0,i} = \frac{a_i}{e_{Q_i, P_i}}$, $\beta_{1,i} = \frac{(1-a_i)}{e_{Q_i, P_i}}$,[8] $\beta_2 = \lambda$, the opportunity cost of capital, $\left(\frac{p^k K_i}{p_i q_i}\right)_t$ is hospital i's capital intensity, and $Z_{i,t}$ is a vector of the hospital characteristics, including

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[7] Subtracting the risk-adjusted cost of capital directly from profitability measures improves the efficiency of estimated coefficients from equation (3.4) [Liebowitz (1987), Ravenscraft and Long (1984)]. Unfortunately accounting data do not contain the risk-adjusted cost of capital.

[8] Notice that I introduce variation in β_{0_i} and β_{1_i} across hospitals by using a set of dummy variables, D_i's, which take a value of one for observations on hospital i and zero otherwise.

variables that stand as proxies for the difference between average and marginal cost. Finally, the $u_{i,t}$ are independent regression errors, with zero mean and variance σ_i^2.

Proxies for the difference between average and marginal cost include the availability of technologically advanced services and the hospital occupancy rate. I also include patient mix variables in $Z_{i,t}$. I assume that the effects of these hospital characteristics on net margin are the same for all hospitals in the sample, and I represent them by $\underline{\beta}$.

Recall from Chapter Two that $Z_{i,t}$ includes patient-mix variables, to test whether or not the community benefit standard constrains the behavior of non-profit hospitals. I interact the for-profit and non-profit ownership dummy variables with the hospital occupancy rate, the percentage of Medicare patients, and the percentage of Medicaid patients, to find out how the effect that these variables have on hospital net margin differs by ownership status.[9] Chapter Two demonstrates that if non-profit hospitals treat more than the profit maximizing quantity of government insured patients, Medicare and Medicaid patients will have a negative effect on non-profit hospital margins, while the effect on for-profit hospital margins will be positive.

I estimate equation (3.6) without an overall constant term because, considering the large number of hospitals in the sample, there is no logical basis for designating an excluded hospital as the base category. By estimating equation (3.6) without a constant

[9] To ascertain which slope variables differ by ownership status, I initially interacted all independent variables with the for-profit and non-profit dummies. Only the interactions with the Medicaid percentage, the Medicare percentage, and the hospital occupancy rate are significant. Subsequent regressions include only these interactions. A Chow test indicates that I cannot reject the hypothesis that the coefficients on the remaining independent variables do not differ by ownership variety ($F_{5,710} = 2.21$).

term, furthermore, I avoid having to adjust the variances of β_{0i} and β_{1i}, thereby simplifying the calculation of the variance of α_i.[10] The remaining slope coefficients do not vary across hospitals or over time. There are no time-invariant independent variables such as teaching status or ownership variety in equation (3.6) because in a fixed effects model the hospital specific dummy variables will reflect the impact of time-invariant variables. As previously discussed in Chapter Two, I incorporate ownership status through interaction with patient mix variables.

I use the following procedure to test whether the estimated conjectural elasticity, $\hat{\alpha}$, is significantly different from zero (one) for each of the 185 hospitals in the sample. The estimate of a hospital's conjectural elasticity, α_i, is

$$\hat{\alpha}_i = \frac{\hat{\beta}_{0i}}{\hat{\beta}_{0i} + \hat{\beta}_{1i}}, \qquad i = 1, \ldots, 185 \tag{3.7}$$

where $\hat{\beta}_{0,i}$ and $\hat{\beta}_{1,i}$ are estimates of the hospital-specific coefficients from equation (3.6). Using the variance-covariance matrix of $\hat{\beta}_{0,i}$ and $\hat{\beta}_{1,i}$ and a Taylor-series expansion, I approximate the variance of $\hat{\alpha}_i$ by

$$\mathrm{V}(\hat{\alpha}_i) = \left[\left(\frac{\partial \alpha_i}{\partial \beta_{0,i}}, \frac{\partial \alpha_i}{\partial \beta_{1,i}}\right)\begin{bmatrix} \mathrm{Var}(\beta_{0i}), & Cov(\beta_{0i}, \beta_{1i}) \\ Cov(\beta_{0i}, \beta_{1i}), & \mathrm{Var}(\beta_{1i}) \end{bmatrix}\left(\frac{\partial \alpha_i}{\partial \beta_{0,i}}, \frac{\partial \alpha_i}{\partial \beta_{1,i}}\right)'\right], \tag{3.8}$$

where $\dfrac{\partial \alpha_i}{\partial \beta_{0i}} = \dfrac{\beta_{1i}}{(\beta_{0i} + \beta_{1i})^2}$, and $\dfrac{\partial \alpha_i}{\partial \beta_{1i}} = \dfrac{-\beta_{0i}}{(\beta_{0i} + \beta_{1i})^2}$.

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[10] Recall that in a fixed effects model with an overall constant term, the coefficients on the firm dummy variables represent the difference in the mean value of the dependent variable between firm i and the omitted firm. The standard errors of the firm dummy variables have a similar interpretation. The sum of the overall intercept and the coefficient on the firm-specific dummy variable provide the overall intercept for an individual firm. The standard error of this intercept will be a function of the standard error of the overall intercept and the standard error of the coefficient on the firm-specific dummy variable. Estimating equation (3.6) without an overall intercept term avoids this complication.

To obtain the estimate of $V(\hat{\alpha}_i)$, $\hat{V}(\hat{\alpha}_i)$, I evaluate these derivatives at $\hat{\beta}_{0,i}$ and $\hat{\beta}_{1,i}$, respectively, and substitute the variance and covariance terms in equation (3.8) with their corresponding estimates.

Denote $\hat{\alpha}_i$, i = 1, … ,185, by $\hat{\boldsymbol{\alpha}}$ and the corresponding variance covariance matrix by $\mathbf{V}(\hat{\boldsymbol{\alpha}})$. Because $\hat{\boldsymbol{\alpha}}$ is asymptotically multivariate normal, quadratic forms constructed on individual elements of $\hat{\boldsymbol{\alpha}}$ are asymptotically $\lambda^2_{(1)}$ when $\boldsymbol{\alpha} = 0$. To test the null hypothesis that $\hat{\boldsymbol{\alpha}} = 0$, therefore, I use

$$K_i = \frac{(A_i\hat{\boldsymbol{\alpha}})^2}{A_i\hat{\mathbf{V}}(\hat{\boldsymbol{\alpha}})A'_i}, \tag{3.9}$$

where A_i is an 1 x 185 vector whose elements are all zero except for the ith element, which is 1, and $\hat{\mathbf{V}}(\hat{\boldsymbol{\alpha}})$ is the estimate of $\mathbf{V}(\hat{\boldsymbol{\alpha}})$.[11] Under the null hypothesis of $\alpha_i = 0$, K_i is asymptotically $\lambda^2_{(1)}$. The corresponding alternative hypothesis is that $\alpha_i > 0$. Recall that this set of hypotheses tests for Cournot behavior by identifying α_i's that are significantly greater than zero.

A modified version of equation (3.9) tests for collusion. Recall that an α_i that is not significantly different from one indicates collusion. The corresponding null hypothesis is $\hat{\boldsymbol{\alpha}} = 1$, against the alternative hypothesis, $\hat{\boldsymbol{\alpha}} \neq 1$. The associated test statistic is

$$K'_i = \frac{(A_i\hat{\boldsymbol{\alpha}} - 1)^2}{A_i\hat{\mathbf{V}}(\hat{\boldsymbol{\alpha}})A'_i}. \tag{3.10}$$

[11] $\mathbf{V}(\hat{\boldsymbol{\alpha}})$ is a 185 X 185 matrix. A Taylor series expansion for i = 1, … 185 provides the diagonal elements. It is not necessary to use the off-diagonal elements of $\mathbf{V}(\hat{\boldsymbol{\alpha}})$ to calculate the test statistic in equation (3.9).

Under the null hypothesis of $\hat{\alpha} = 1$, K'_i is asymptotically $\lambda^2_{(1)}$. Chapter Five reports results of the significance tests from equations (3.9) and (3.10). Overall, I reject Cournot behavior for the majority of the hospitals in the sample, but I cannot reject collusive behavior.

CHAPTER FOUR

Description of the Data and Definition of Variables

I. Description of the Data

The Florida Agency for Healthcare Administration provided the data that I use in this dissertation. This agency requires all Florida hospitals to report financial information and patient discharge data. Hospitals (short-term general, teaching, and other specialty hospitals, and long-term general hospitals) submit patient discharge data quarterly and financial data annually. The financial and hospital characteristics data cover the period 1990-1993, inclusive. I use patient discharge data from the first quarters of 1990 and 1993.

There are 207 reporting hospitals in existence throughout the sample period 1990-1993. The agency classifies 197 (95 percent) of these hospitals as short-term general facilities, with the rest being either long-term general, teaching, or specialty facilities. Specialty hospitals include women's and children's facilities as well as centers that concentrate on certain diseases, such as cancer institutes. I include these specialized hospitals in the sample because it is probable that they compete with short-term general hospitals for some primary and secondary care services [Zwanziger, *et al.* (1994)]. The degree of competition between specialized and general facilities is probably greatest for women's and children's centers.

Of the 207 reporting hospitals, 189 provide complete data over the sample period. I remove the two monopolist hospitals from the sample because for such hospitals distinguishing between the efficiency and collusion hypotheses is meaningless.

Two additional hospitals have erroneous discount data (discounts of over 100 percent). I use the remaining 185 hospitals to estimate the model that Chapter Three describes.

A. Calculation of Hospital Geographic Markets

(i). Method

I use patient origin data to define the geographic markets following the shipments method that Elzinga and Hogarty (1973) describe. This method defines a self-contained market area in which few patients go outside the area for treatment ("little out" from inside) and few travel into the area for treatment ("little in" from outside).

I use a seventy percent cut off point[1] to define the boundaries for each hospital's geographic market. As an intermediate step in this process, I calculate the number of discharges per zip code for each hospital. The University of Alabama School of Public Health in Birmingham used this data to calculate hospital geographic markets following the shipments method. The school provides this description of the program that they used to create the geographic markets:

> The program works by creating a geographic market matrix for each producer [hospital]. Locations are added in sequence (largest to smallest) to the producer's market area until the specified cut off portion [seventy percent] of the transactions [discharges] is reached. This is the horizontal matrix function. The program then adds to this market area all of the competing producers whose product is also purchased by the residents of the same locations. This continues until the set of competitors who are used by . . . seventy percent of the residents of the area is identified. This is the vertical matrix function. The program then returns to the horizontal function to identify the locations that are part of the geographic market area of each competing producer. This continues until each of the competitors' markets is identified to the . . . seventy percent level. The program returns to the vertical function to find the set of competitors to the competitors in their market areas. The program alternates between

[1] Each hospital's geographic market contains seventy percent of the hospital's discharges.

> the horizontal and vertical matrix functions until an area is identified where . . . seventy percent or more of the product produced locally is purchased locally, and where . . . seventy percent or more of the product purchased locally is produced locally.

In addition to the shipments method, one also may use either the radius method or geopolitical boundaries to define hospital geographic markets [Morrisey, *et al.* (1989), Garnick, *et al.* (1987)]. The radius method is based on physician willingness to travel [Robinson and Luft (1988, 1987)] and considers hospitals within fifteen miles of each other to be in the same market. While this method may be appropriate for emergency room services, a fifteen mile distance may not be relevant for scheduled procedures or for all kinds of hospitals [Garnick, *et al.* (1987)]. Patients may be willing to travel more than fifteen miles, furthermore, for a "preferred bundle of physician-hospital services" [Morrisey, *et al.* (1989)].

These artificial boundaries do not accurately reflect hospital markets. Geopolitical boundaries, such as counties or statistical metropolitan areas (SMSAs), may understate the amount of competition in rural areas and overstate the amount of competition in urban areas where all hospitals in the market may not actually be competitors [Zwanziger, *et al.* (1994), Morrisey, *et al.* (1989), Garnick, *et al.* (1987)]. SMSAs, moreover, represent labor markets not hospital markets [Garnick, *et al.* (1987)].

Patient origin data, by contrast, measures actual competition [Garnick, *et al.* (1987)] and is based on patient willingness to travel [Morrisey, *et al.* (1989)]. This method is superior to either the radius method or use of artificial boundaries, because it can create geographic markets for various kinds of patients or services [Garnick, *et al.* (1987)]. The primary disadvantage of this method is that it is a static method of

classification. Hence, it cannot measure patient response to a price increase by the provider. Specifically it cannot detect whether a patient will switch providers if a payor drops its current provider from the network because of a price increase [Zwanziger, *et al.* (1994)]. This relative bargaining power is important in the negotiation of managed care contracts [Zwanziger, *et al.* (1994), Melnick, *et al.* (1992)].[2]

(ii). Patient Base

This analysis focuses on the relationship between hospital market structure and profitability of managed care contracts. I use privately insured, PPO, and HMO discharges, therefore, to calculate each hospital's geographic market. I calculate two geographic market boundaries using first quarter 1990 and first quarter 1993 discharges, respectively. I use the 1990 boundaries to compute market share and the hospital-specific Herfindahl index for both 1990 and 1991. Similarly, I use the 1993 boundaries for 1992 and 1993 market share and Herfindahl indices. Although I hold the geographic market boundaries constant for these two year periods, a hospital's market share does vary annually. Using a weighted average of four quarters of discharge data to create annual geographic markets would be ideal, but it also would be prohibitively expensive.

Table 4.1 compares the payor mix distributions for the first quarters of 1990 and 1993.[3] Over this time period the percentage of privately insured patients remains relatively constant, representing 36.7 percent of discharges in the first quarter of 1990

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[2] Managed care contracts are typically yearly contracts.

[3] Section III contains all tables pertinent to the analysis in this chapter.

and increasing to 38.6 percent in 1993.[4] PPO/HMO discharges represent 74,458 or 15.4 percent of the discharges for the first quarter of 1993.[5] The percentage of government insured patients also increases over the sample period. The percentage of Medicare discharges increases from 37.8 percent in 1990 to 42.3 percent in 1993.[6] Similarly, Medicaid discharges increase from 10.9 percent in 1990 to 15.8 percent in 1993.[7]

Basing the geographic market on all privately insured and PPO/HMO discharges assumes that the geographic market is the same for all services the hospital offers to these patients. This assumption should not be too limiting because payors presumably contract with hospitals able to provide a wide range of services to minimize their transaction costs.

II. Definition of Variables

A. Definition of Dependent Variables and Their Components

This dissertation uses two dependent variables in various analyses. The dependent variable in equations (3.6) and (6.1) is hospital net margin, while net price is the dependent variable in equation (5.3). I create the dependent variables net price (NTPRICE), and net margin (NMARGIN) for a market basket of inpatient services. The market basket includes eight revenue/cost centers: Medical/Surgical Acute,

[4] In 1993 the percentage of private pay patients is the sum of the commercial insurance, commercial HMO, commercial PPO, and self-insured categories. The data do not provide this level of data in 1990.

[5] The data include PPO and HMO discharges in the commercial insurance category for 1990.

[6] This is the sum of Medicare and Medicare HMO discharges.

[7] This is the sum of Medicaid and Medicaid HMO discharges.

Medical/Surgical ICU, Surgery Services, Anesthesiology, Laboratory Services, Electrocardiography (ECG),[8] Radiology/Diagnostic,[9] and Respiratory Therapy.[10]

I choose these services by calculating the annual mean inpatient revenue by revenue center and identifying services that at least 92 percent[11] of the hospitals in the sample provide and for which the data include units of service.[12] The market basket contains the eight services with the highest mean inpatient revenue. The market basket services account, on average, for 56 percent of hospital inpatient revenue.[13]

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[8] The Florida Agency for Healthcare Administration defines "electrocardiography" to be "the operation of specialized equipment to record graphically: (1) electromotive variation in actions of the heart muscle; (2) the direction and magnitude of the electrical forces of the heart's action; (3) the sound of the heart for diagnostic purposes; and (4) the electromotive variations in brain waves.

[9] The Florida Agency for Healthcare Administration defines "Radiology-Diagnostic" services to include the taking, processing, examining, and interpreting of radiographs, ultrasonograms, and fluorographs

[10] The Florida Agency for Healthcare Administration defines respiratory therapy as the "administration of oxygen and certain potent drugs through inhalation of positive pressure and other forms of rehabilitative therapy. Services also include pulmonary function testing, the testing of patients through measurement of inhaled and exhaled gases and analysis of blood, and evaluation of the patient's ability to exchange oxygen and other gases."

[11] I choose 92 percent to hold constant the services included in the market basket in each year of the sample period.

[12] Units of service also had to be available for each service in the market basket for me to calculate unit price and average cost. For example, inpatient days are the relevant unit for medical/surgical acute inpatient revenue. Similarly, minutes are the appropriate units for anesthesiology revenue.

[13] Following Dranove, *et al.* (1993) I calculate these percentages excluding inpatient revenue from Psychiatric Long-term Care, Psychiatric ICU, and Residential Care because facilities other than general acute care hospitals often provide these kinds of services.

(i). Components

Computing a hospital's net margin requires construction of three intermediate variables: unit price, unit cost, and percentage discount. I now discuss the calculation of these intermediate variables.

Discount from Charges **(DISC)**

Providers will institute discounts from charges to HMOs and PPOs in return for an expected increased volume from these payors' insured populations. The hospital's margin should reflect these discounts. I define DISC as [(Revenue Deductions (exclusive of bad debt) from Commercial HMOs, PPOs, and Other Discounted Payors)/ (Total Revenue from Commercial HMOs, PPOs, and Other Discounted Payors)]*100. This is an average discount, reflecting all commercial discounted payors. DISC also incorporates both inpatient and outpatient revenue, implicitly assuming that the same percentage discount applies to both kinds of service. Such an assumption is necessary because the data provide only aggregate contractual allowances by major payor category (Commercial PPO, Commercial HMO, and Other Discounted Payors). To isolate discounts hospitals grant on inpatient services, I adjust DISC to incorporate the relative importance of commercial HMO and PPO inpatient revenue. I define DISC1 as DISC* (Commercial HMO and PPO Inpatient Revenue/ Commercial HMO, PPO and Other Discounted Payors Total Revenue).[14] For the small number of hospitals with contractual

[14] The numerator of the adjustment to DISC does not include Inpatient Revenue from Other Discounted Payors because the data do not separate the Revenue from Other Discounted Payors into inpatient and outpatient categories. This omission, therefore, will slightly understate the inpatient adjustment to DISC. I cannot calculate an inpatient adjustment if "Revenue from Other Discounted Payors" is the only kind of discounted revenue. For these cases DISC = DISC1.

allowances but no corresponding revenue from commercial PPOs and HMOs, I calculate DISC as a percentage of charge based revenue.[15]

Unit Gross Price for Inpatient Services in the Market Basket

The financial data provide total inpatient revenue by major revenue/cost center and also units of service for all services in the market basket. Because the data provide only total units of service, I adjust the units of service data to reflect only inpatient units of service. For each revenue center in the market basket, the adjusted units of service equal (total units of service) * (inpatient revenue/total revenue). I define the unit gross price for each service in the market basket as (total inpatient revenue/adjusted units of service).

Average Variable Cost for Inpatient Services in the Market Basket (UNTCOST)

Hospitals separate revenue data into inpatient and outpatient categories, but they do not do so for cost data. I assume, therefore, that average variable cost is the same for market basket services that hospitals provide to either inpatients or outpatients. For each service in the market basket, I define average variable cost as (total variable expense/units of service). Total variable expense includes salaries, wages, fringe benefits, and other variable expenses associated with each cost center. Notice that the hospitals do not include depreciation, amortization, and lease expenses in the cost center expenses. The average variable cost of the market basket, therefore, is a good proxy for marginal cost.

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[15] For these hospitals, DISC=DISC1, because the data do not separate charge based revenue into inpatient and outpatient components.

(ii). Dependent Variables

Net Price of the Market Basket (NTPRICE)

I calculate the gross price (GRPRICE) of the market basket in each year by weighting the average price of each service in the market basket by its relative importance and summing across services. I compute the weights on an annual basis. [16] In each year of the sample period, Medical/Surgical Acute and Laboratory Services are the two largest components of the market basket.

I adjust the gross price of the market basket to reflect the contractual allowances that hospitals grant. NTPRICE equals [GRPRICE * (1-DISC1)].

Net Margin Earned on the Market Basket (NMARGIN)

The gross margin (GMARGIN) that hospitals earn on the market basket of services equals (GRPRICE - UNTCOST)/GRPRICE. I define the net margin that hospitals earn on the market basket (NMARGIN) as GMARGIN * (1-DISC1).

B. Definition of Independent Variables and Their Expected Sign

Market Share **(MS)**

A hospital's market share is its percentage of the total privately insured inpatient days for intensive, acute, and subacute care in its market. The privately insured patient base includes charge-based patients, HMO/PPO patients, and other patients for whom the hospital receives discounted reimbursement. Each hospital has an average of seven competitors in both the 1990 and 1993 definition of its market, although the identity of

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[16] For each year I calculate the percentage composition of the mean market basket revenue. These percentages become the weights.

its competitors changes substantially over this time. The maximum number of competitors in a market is 34 hospitals for the markets using 1990 discharges and 36 hospitals for the markets using 1993 discharges. Recall that I calculate hospital market share annually. I expect higher share hospitals to have higher margins.

Adjusted Market Share **(ADJMS)**

Given the prevalence of for-profit chain hospitals, some hospitals located within the same market may have common ownership, which may result in larger values of α_i, the hospital's estimated conjectural elasticity, even in the absence of collusion among independent hospitals. I recalculate market share to incorporate this common ownership. Within a hospital's market I group Humana hospitals together to calculate an adjusted market share that considers hospitals that this company owns to be one entity. I do the same for both HCA and AMI hospitals. These three groupings affect 98 hospital markets for 1990 and 1991 and 47 hospital markets for 1992 and 1993. This dissertation uses this measure of market share in all subsequent analyses.

Herfindahl index **(HHI)**

I create a hospital-specific Herfindahl index because each hospital has its own geographic market. Other studies on hospital competition also use hospital-specific measures of concentration. [Melnick, *et al.* (1992), Zwanziger and Melnick (1988), Melnick and Zwanziger (1988)].[17]

[17] These authors create service-specific geographic markets. They identify service categories by combining all DRGs that the same kind of physician would provide. For each hospital they identify zip codes that comprise at least three percent of the discharges for each service category. They classify competing hospitals as those that comprise at least three percent of any ZCA's [zip code area] total discharges for any service category in a ZCA that is in another hospital's market area. They then create a Herfindahl index for each service category in each zip code and calculate a Herfindahl for each hospital:

Adjusted Herfindahl index **(ADJHHI)**

ADJHHI equals a hospital's Herfindahl index adjusted to reflect any hospitals having common ownership located within a hospital's market. All of the regressions in Chapters Five and Six use this measure of market concentration as a regressor.

Patient Mix Variables **(MCARESH, MCAIDSH, KSHARE)**

MCARESH, MCAIDSH, and KSHARE are a hospital's percentage of Medicare, Medicaid, and PPO/HMO inpatient days, respectively. The effect of the percentage of either Medicare or Medicaid patients on the price-cost margins of services that hospitals provide to privately insured patients is indeterminate. If hospitals with a high percentage of Medicare or Medicaid patients provide a lower quality of care, the sign of the estimated coefficient will be negative, reflecting that the hospital must accept a lower price arising from below average quality. Alternatively, if a hospital possesses market power, it may be able to increase the price of its services to privately insured patients, to compensate for the lower reimbursement for treatment of Medicare and Medicaid patients.

The effect of a hospital treating a large percentage of HMO/PPO patients on price-cost margins is also indeterminate. If a hospital depends on managed care patients to maintain its patient base, it may not have significant bargaining power with a payor. But, a high percentage of PPO/HMO patients may indicate that a hospital is important to

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> [A] hospital's weighted average HHI [Herfindahl] is calculated for each service by summing the average HHI for the ZCAs [zip codes] in the relevant service market weighted by the proportion of the hospital's discharge for that service that originate in the ZCA. Then the overall HHI for the hospital is the weighted average service HHI, weighted by the proportion of the hospital's discharges accounted for by the service [Zwanziger and Melnick (1988) at 312].

one or more managed care networks, thereby increasing its bargaining power with those insurers.

Hospital occupancy rate **(HOCCUP)**

A hospital's capacity limits the number of patients it can serve. The potential inpatient days that the hospital can provide is the number of available beds multiplied by 365. A hospital's occupancy rate, therefore, reflects the amount of its capacity that the hospital actually uses. I define HOCCUP as [(total inpatient days/potential inpatient days) * 100]. The effect the hospital occupancy rate has on net margin is indeterminate. A positive coefficient may reflect either the market power or higher quality of a high occupancy hospital. Alternatively, a positive coefficient may reflect the lower costs of economies of scale production. A negative coefficient may indicate a hospital's willingness to accept a lower price given sufficient patient volume from a managed care network.

Ownership Characteristics **(PROFIT, NOPROFIT)**

I use dummy variables to indicate the ownership status of each hospital. NOPROFIT takes a value of one for non-profit hospitals, and zero otherwise. PROFIT takes a value of one for all investor-owned hospitals and zero otherwise. Government hospitals are the excluded category.[18] These variables are regressors in the cross-section regressions in Chapter Six and the price equations of Chapter Five.

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[18] If a series of dummy variables identifies for-profit, non-profit, and government hospitals, perfect multicollinearity will result. To avoid perfect multicollinearity, I do not use dummy variables to identify government hospitals. The estimated coefficient on PROFIT, for example, therefore represents the difference in the net margin of for-profit and government hospitals. The estimated coefficient on NOPROFIT has a similar interpretation.

Relative to government hospitals, for-profit and non-profit hospitals should have higher margins because of either lower quality or lower reimbursement in government hospitals. By controlling for case-mix, I can eliminate the possibility that government hospitals have lower margins relative to both for-profit and non-profit hospitals because government hospitals provide different kinds of services.

The relative magnitudes of the PROFIT and NOPROFIT coefficients are indeterminate. For-profit hospitals may have higher costs relative to not-for-profit hospitals, presumably because of the non-profits' tax exempt status and ability to issue tax-exempt bonds. Alternatively, for-profit hospitals may be more efficient or charge higher prices than do their non-profit counterparts.

Because the fixed effect model that equation (3.6) estimates cannot have any time invariant variables as regressors, I interact PROFIT and NOPROFIT with MCARESH, MCAIDSH, and HOCCUP, to form the variables PRMCARE, NPRMCARE, PRMCAID, NPRMCAID, POCCUP, and NPOCCUP. These ownership interaction variables incorporate ownership into equation (3.6). I also include these ownership interaction terms in a version of equation (6.1) to test the hypotheses concerning non-profit hospital behavior and the community benefit standard that Chapter Two describes.

***Sophisticated Services* (HITECH)**

The AHA *Guide* provides an extensive list of the services that each reporting hospitals offers. I consider these eight facilities/services[19] to be technologically advanced: cardiac catheterization laboratory, open-heart surgery, certified trauma center,

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[19] The list of chosen services is similar to those that recent studies on hospital competition [Dranove, *et al.* (1993)] and hospital cost functions [Zuckerman, *et al.* (1994)] use.

extracorpeal shock-wave lithotripter (ESWL), neonatal intensive care unit, megavoltage radiation therapy, magnetic resonance imaging (MRI), and organ/tissue transplants.[20] For hospitals reporting to the AHA, the variable HITECH identifies the number of these eight services available at each hospital.

If in any one year during the sample period, a hospital does not report[21] data to the AHA, I use these procedures to create the variable HITECH. If the hospital reports data in both the previous and following years to the missing year, and the number of advanced services it offers does not change over this time period, HITECH takes the value of services the hospital offers in the previous (or equivalently, following) year for the nonreporting year. If the hospital is nonreporting for two sequential years, or the number of advanced services it offers in the years both prior to and following the nonreporting year differ, I use the Florida Agency for Health Care Administration hospital financial data to create the HITECH variable. The hospital financial data contain a less comprehensive list of hospital services than does the AHA Guide, identifying only a

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[20] The AHA Guide provides these definitions:

Cardiac catheterization laboratory :"Provides special diagnostic procedures necessary for the care of patients with cardiac conditions. Available procedures include introduction of catheter into the interior of the heart through a vein or artery or by direct needle puncture" [AHA Guide (1994) at A9].

Extracorpeal shock-wave lithotripter: "A medical device used for treating stones in the kidney or ureter. Kidney stones are disintegrated non-invasively through the transmission of acoustic shock waves directed at the stones" [*Ibid.*].

Megavoltage radiation therapy: "The use of specialized equipment in the supervoltage and megavoltage (above 1 million volts) ranges for deep therapy treatment of cancer" [*Ibid.* at A11].

Magnetic resonance imaging: "The use of a uniform magnetic field and radio frequencies to study tissue and structure of the body" [*Ibid.*].

[21] A classification of "nonreporting" means that the hospital returned the survey to the AHA after the cutoff date for statistical processing.

subset of technologically advanced services: neonatal intensive care unit, open-heart surgery, cardiac catheterization laboratory, and MRI. For these hospitals the variable HITECH is the number of this subset of services offered, and therefore, I most likely understate the degree of technical sophistication for this group of hospitals.[22]

The effect on hospital margins of offering technologically advanced services remains uncertain. Margins may be lower because of the high cost of providing these services. Alternatively, hospitals may be able to charge a price premium for their state of the art facilities.

***Case-Mix Index* (CASE)**

The Florida Agency for Health Care Administration calculates annual case-mix scores for each hospital. This measure captures the variation in patients' conditions at each hospital. The case mix score is the summation of the product of the discharges for each DRG, multiplied by a weight for each DRG, divided by the hospital's total discharges. The agency uses the Medicare weights, which the Health Care Financing Association calculates, to weight the DRGs.

The effect of a high case mix score on hospital margins is uncertain. A hospital that offers a wide variety of services, thereby treating a large cross section of DRGs, and that has patients who are sicker, on average, than are patients at other hospitals, may have higher costs, and therefore lower margins. Alternatively, a hospital that can treat a variety of DRGs might extract a price premium, because an insurer can reduce its contracting and administrative costs by interacting with fewer hospitals.

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[22] This should not seriously affect the results, because most of hospitals in the sample reported data to the AHA.

Capital Intensity **(CAPINTEN)**

A hospital's capital intensity reflects its use of fixed assets. Chapter Three discusses the motivation for and the effects of including this variable as a regressor in a net margin equation. Surprisingly, in many inter-industry studies, the coefficient on the capital intensity variable is significantly negative [Liebowitz (1987)]. Researchers often interpret the negative coefficient in this manner: holding total costs constant, the higher is the capital-sales ratio, the lower the average variable costs must be [Dranove, *et al.* (1993)].

Hospital capital intensity equals the ratio of long-term assets to revenue. The denominator is the gross revenue on the market basket of inpatient hospital services. The numerator is the original cost of property, plant, and equipment from the hospital's balance sheet. Ideally, the capital intensity variable should reflect the current market value of long-term assets. The balance in the hospital plant and equipment fund approximates market value. The data, however, do not provide this information. This proxy would not be available for for-profit hospitals, furthermore, because only non-profit hospitals use fund accounting.

C. Variables Used in the Analysis of the Hospital's Conjectural Elasticity

Because the significance tests in equations (3.9) and (3.10) only identify the departure from Cournot behavior and collusion, respectively, I also estimate two probit models to ascertain the factors that contribute to cooperative behavior. Equations (5.2a)

and (5.2b) describe the dependent variables. The rest of this section describes the independent variables unique to this analysis.

(i). Market Structure Variables (AVGAMS, AVGAHHI, MARKDOM)

The variables AVGAMS and AVGAHHI measure a hospital's average adjusted market share and average adjusted Herfindahl index over the sample period. A statistically significant, positive relationship between the average adjusted Herfindahl index and the dependent variables in equations (5.2a) and (5.2b) provide evidence of collusion [Clarke, *et al.* (1984)]. That is, the more concentrated a hospital's market is, the more likely that the hospital will engage in cooperative behavior. Conversely, a statistically significant positive AVGAMS coefficient in a regression with the dependent variable as equation (5.2a) defines it, supports the differential efficiency hypothesis. High market share hospitals commonly are the dominant firms in a market, and therefore they are not likely to adopt Cournot behavior.

MARKDOM captures the effect that a dominant hospital has on other hospitals in a market. A dominant hospital is one with no large rivals. A hospital has no large rivals if its share of the market is at least ten percent greater than that of any other hospital in the market. MARKDOM takes a value of one if a hospital is in a market with a dominant hospital and zero otherwise. In 1990 43 hospitals share a market with a dominant hospital. By 1993 the number of markets with a dominant hospital increases to 52. I also use this variable as a regressor in the price equation, to see if the presence of a

dominant hospital in a market creates an umbrella under which competing hospitals can earn economic rent by charging higher prices.

(ii). Other Hospital Characteristics

Urban\Rural Indicator **(LOCATION)**

I use the Department of Agriculture's urban/rural continuum to find out if the significance of a hospital's conjectural elasticity varies by geographic location. This county-level classification is based on SMSAs (Statistical Metropolitan Areas) and has values ranging from zero to nine, with zero being the most populated urban areas and nine representing the most thinly populated rural areas.[23]

Hospital Size **(BIG)**

To find out if larger hospitals are more likely to act cooperatively, I include hospital size as an independent variable. The mean hospital bed size for the sample is 250. I define BIG, therefore, to be equal to one if a hospital has 250 or more staffed beds as of year end 1993 and zero otherwise

[23] A county with a classification of zero is a large metropolitan core county of a large SMSA, with a population exceeding 1,000,000. A classification of four indicates an urbanized non-metropolitan county that is adjacent to a SMSA and has between 20,000 and 249,999 urban residents. A county with a classification of nine is a thinly populated county, not adjacent to a SMSA, having fewer than 2,500 urban residents. The Department of Agriculture defines "adjacent" as: Counties physically adjacent to one or more SMSA's and having at least two percent of the employed labor force in the nonmetropolitan county commuting to central metropolitan counties.

D. Variables Unique to the Price Function

To ascertain the effects that hospital behavior and market structure have on hospital prices, I estimate a price function as equation (5.3) describes. The rest of this section describes the independent variables unique to this analysis.

(i). Behavior Variables (ASIGN, ASIGN1)

The variables ASIGN and ASIGN1 depict hospital cooperative behavior. Using the results from the chi-squared test in equation (3.9), ASIGN equals one if the hospital's conjectural elasticity is significantly different from zero. Similarly, from the chi-squared test in equation (3.10), ASIGN1 equals one if the hospital's conjectural elasticity is not significantly different from one. If cooperative behavior enables hospitals to charge higher prices, the coefficients on these behavior variables will be positive.

(ii). Other

***Regional Differences* (URBAN)**

The dummy variable, URBAN, takes a value of one for counties with classifications of zero, one, two, or three on the Department of Agriculture's urban/rural continuum.

***Teaching Status* (TEACH)**

I obtain a hospital's teaching status from the annual American Hospital Association (AHA) *Guide to the Health Care Field*. The dummy variable, TEACH, takes a value of one if a hospital is a teaching hospital and zero otherwise. I classify a hospital as a teaching hospital if it has an approval code of three, five, or eight in the

AHA *Guide*. An approval code of three indicates that the Accreditation Council for Graduate Medical Education has approved the hospital to participate in residency training. A five indicates medical school affiliation. Hospitals with an approval code of eight are members of the Council of Teaching Hospitals of the Association of American Medical Colleges. Membership in the council is relatively rare.

The effect of teaching status on price is indeterminate. Teaching hospitals may receive lower prices because of perceived poor quality because residents provide some services. Alternatively, if the teaching hospital provides sophisticated, complex services that are unavailable at other hospitals, it may have market power in the privately insured market and be able to charge more for its services.

III. Tables

A. Table 4.1

Patient Mix

1st Quarter 1993

Payor	# of Discharges	Percentage
Medicare	192,173	39.8 %
Medicare HMO	12,138	2.5 %
Medicaid	71,718	14.8 %
Medicaid HMO	4,714	1.0 %
Commercial Insur.	76,737	15.9 %
Commercial HMO	37,601	7.8 %
Commercial PPO	36,857	7.6 %
Self-pay/Charity	35,481	7.3 %
Other	15,759	3.3 %
TOTAL	483,178	100.0 %

1st Quarter 1990

Payor	# of Discharges	Percentage
Medicare	179,087	37.8 %
Medicaid	51,738	10.9 %
Commercial Insur.	173,999	36.7 %
Other	69,521	14.6 %
TOTAL	474,345	100.0 %

Notes: I obtain the data in this table from the first quarter 1990 and 1993 patient discharge data that Florida hospitals submit to the Florida Agency for Healthcare Administration. The "Other" category in 1993 includes Champus, VA, and worker's compensation discharges. The 1990 "Other" category includes these categories as well as other discharges. The 1990 data do not provide as detailed payor information.

CHAPTER FIVE

Fixed Effects, Probit, and Price Function Estimation

I. Introduction

This chapter uses a fixed effects model to estimate the parameters necessary to calculate each hospital's conjectural elasticity and to test for competitive, collusive, or Cournot behavior. I categorize the results of these tests using a variety of hospital and geographic characteristics. To identify the factors contributing to cooperative behavior, I also estimate two probit models. These models analyze the effect of market structure on hospital behavior by including market share and the Herfindahl index as regressors. I construct the dependent binary variables for these models using the results from the initial significance tests. These variables approximate collusion or the departure from Cournot behavior. Finally, to ascertain the effect that hospital behavior and market structure have on pricing, I also estimate a hospital price function.

II. Descriptive Statistics

Table 5.1 provides a list of variable definitions.[1] Table 5.2 contains the annual descriptive statistics for the 185 hospitals in the sample from both 1990 and 1993, the first and last years of the panel data set. The patterns of change in net prices, costs, and concentrations are of interest. Over the sample period there is a 9.39 percent increase in average net price of the hospital market basket (NTPRICE) from 903.61 in 1990 to

[1] Section V contains all tables pertinent to the analyses in this chapter.

988.42 in 1993. The unit cost (UNTCOST) of the market basket, by contrast, increases only 6.7 percent, from 617.84 in 1990 to 659.21 in 1993.

Not only do hospital prices increase more than costs, but also hospital prices increase in spite of an increase in the average percentage of managed care patients (KSHARE) from 9.56 percent in 1990 to 11.91 percent in 1993. Increased managed care penetration is supposed to increase price competition among hospitals. The relative increase in both prices and costs implies that hospitals are able to pass on any increased costs in spite of increased managed care penetration. The increases in both NTPRICE and KSHARE, moreover, may indicate that networks do not choose hospitals solely on the basis of price and that as a hospital becomes more important to a network, in terms of the number of patients served, the hospital's bargaining power with the insurer may increase.

Accompanying the growth in managed care patients is an increase in the average percentage of Medicare patients (MCARESH), from 54.30 percent in 1990 to 57.91 percent in 1993. In spite of the increase in Medicare patients, the average hospital occupancy rate (HOCCUP) declines from 52.5 percent in 1990 to 49.7 percent in 1993.

Markets also grow more concentrated over the sample period. The average adjusted Herfindahl index (ADJHHI) increases 4.36 percent, from 2683.8 in 1990 to 2800.9 in 1993. This variable, which appropriately reflects the effect of common ownership in multi-hospital systems on market structure, shows a higher level of market concentration than does the unadjusted Herfindahl index (HHI). Notice that, in spite of a lower level, the unadjusted Herfindahl index shows a greater change in concentration

over the sample period than does the unadjusted index. The unadjusted Herfindahl index increases 8.52 percent over the sample period, from 2539.8 in 1990 to 2756.2 in 1993. These relative changes, therefore, illustrate that it is important to incorporate the common ownership of multi-hospital systems into measures of market concentration to reflect market structure accurately.

III. Results

A. Fixed Effects Model

I estimate equation (3.6) for 185 hospitals (i = 1, ..., 185) for the years 1990 through 1993 (t = 1, ...,4). As Chapters Two and Three observe, I incorporate the effects of ownership into the model by interacting the ownership dummy variables with HOCCUP, MCAIDSH, and MCARESH. The resulting interaction variables, which I define in Table 5.1, are POCCUP, NPOCCUP, PRMCARE, NPRMCARE, PRMCAID, NPRMCAID.[2] Tables 5.3 and 5.4 contain the estimation results.[3]

Table 5.3 reports the estimates of all coefficients except the hospital-specific intercept and market share coefficients, which Table 5.4 lists. The overall insignificance of the estimated coefficients in Table 5.3, with the exception of KSHARE, DUM91, and DUM93, is not surprising because fixed effects estimation considers only within-hospital

[2] In spite of the insignificance of these variables in Table 5.3, their inclusion does affect the hospitals' λ^2 statistics from equation (3.9). I re-estimated equation (3.6) excluding the ownership interaction variables. In comparing the results of the significance tests from these two specifications, 17.84 percent of the estimated conjectural elasticities change significance when I include the ownership interaction variables in equation (3.6).

[3] Recall that all tables are located in Section V.

variation. Increasing the number of years included in the panel could improve the precision of the estimation.

I use the hospital-specific intercepts and market share coefficients to obtain each hospital's conjectural elasticity based on the relationship in equation (3.7). It is important to realize the difference between the theoretical and empirical interpretations of a hospital's conjectural elasticity. Theoretically, a hospital's conjectural elasticity is its expectation concerning rivals' responses to changes in its output level. Because this expectation is unobserved, an estimate of the conjectural elasticity reveals "how close to a completely collusive outcome the expectations induce" [Bresnahan (1989) at 1029]. Therefore,

> the estimated [conjectural elasticities] tell . . . us about price and quantity setting behavior; if the estimated "conjectures" are constant over time and if breakdowns in the collusive arrangements are infrequent, we can safely interpret the parameters as measuring the average collusiveness of conduct [*Ibid.*]

Table 5.4 lists the estimated conjectural elasticities, their components, the associated standard errors, and a ten percent confidence interval for the estimated conjectural elasticities for approximately 71 percent of the sample (131 hospitals). Table 5.4 does not include the remaining 54 hospitals because their estimated confidence intervals are too wide to be meaningful.[4] These confidence interval are wide because the standard error of the estimated conjectural elasticity is large. Recall that I use a Taylor series expansion to estimate the variance of the estimated conjectural elasticity. This expansion has an asymptotic justification, but its use may lead to an exaggerated standard error in finite samples.

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[4] For example, a confidence interval spanning (-5.46, 5.85).

Table 5.4 illustrates that many hospitals have an estimated conjectural elasticity that exceeds one, indicating more than perfect coordination among hospitals. Overall, 67 percent of the hospitals in the sample have an estimated conjectural elasticity that exceeds one. Equation (3.7) illustrates that this result occurs when the hospital-specific market share coefficient is negative. Focusing on statistical significance rather than numerical value, I test the null hypothesis that the conjectural elasticity equals one against the alternative hypothesis that it is greater than one. I can reject the null hypothesis at a five percent significance level for only 34 or 18.38 percent of the 185 hospitals in the sample. This percentage is substantially less than the 67 percent of hospitals that have an estimated conjectural elasticity greater than one in numerical value. I focus here, therefore, on the statistical significance of a hospital's estimated conjectural elasticity rather than on the numerical value of the estimated conjectural elasticity.

To test if α_i is significantly different from zero (one), I use the chi-squared statistics in equation (3.9) (equation (3.10)). As Chapter Two discusses, a conjectural elasticity equal to zero represents Cournot behavior, while a value of one indicates collusion.[5] Rather than reporting the results of these significance tests for each individual hospital, I summarize them according to various hospital characteristics and geographic factors in Tables 5.5, 5.6, 5.6A and 5.7.

Table 5.5 categorizes the results of the significance tests for Cournot behavior, from equation (3.9), according to ownership status, bed size, geographic region, and

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[5] For completeness I also consider the possibility that hospital markets are perfectly competitive. A conjectural elasticity of negative one indicates perfect competition. I reject perfect competition for approximately 84 percent of hospitals in the sample.

level of market concentration. This table classifies hospitals into one of two groups according to the results of the significance tests in equation (3.9). Group I contains hospitals for which I can reject Cournot behavior while hospitals in Group II hold Cournot conjectures. This table reads as follows: From column three, 46.81 percent of the hospitals for which I reject the null hypothesis, H_0: $\alpha = 0$, are for-profit hospitals, 43.97 percent are non-profit hospitals, and the remaining 9.22 percent are government hospitals. Approximately 89 percent of these hospitals are in urban areas with an average bed size of 268. The average Herfindahl index for this group of hospitals is 2723. Column four has a similar interpretation. For comparative purposes column two provides the percentages and means for these descriptive characteristics for the entire sample.[6]

From Table 5.5, column three, I reject Cournot behavior, based on a conjectural elasticity that is statistically different from zero at the five percent level, for 141, or 76.22 percent, of the hospitals in the sample.[7] A comparison of columns three and four reveals that, on average, these hospitals are likely to be larger (268 versus 181 beds), and more likely to be located in urban areas (88.65 percent versus 77.27 percent) than are those hospitals that adopt Cournot behavior. Characterization by ownership is not especially revealing, perhaps because for-profit hospitals dominate the sample.

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[6] Notice that the Herfindahl in this table reflects the common ownership of multi-hospital systems.

[7] Recall from Chapter Three that I consider this to be a one-tailed test. The corresponding alternative hypothesis is that $\alpha_1 > 0$. From Chapter Two, I define α to be between zero and one. Very few of the estimated conjectural elasticities are less than zero.

The most interesting result of Table 5.5 is that hospitals that do not follow Cournot behavior are located in somewhat less concentrated markets than are those hospitals that adopt Cournot behavior, as the average Herfindahl index for hospitals for which I reject the null hypothesis of $\alpha = 0$ is 2723, which is smaller than the average Herfindahl index of 2789 for hospitals for which I cannot reject the null hypothesis. The difference in concentration levels is even more pronounced for urban hospitals (2628 versus 2861).[8] This relationship between market structure and departure from Cournot behavior indicates that hospitals in less competitive (more concentrated) hospital markets do not expect rival hospitals to respond to their output choices. Such a result implies that hospitals ignore departures from any collusive agreements. Stigler (1964) argues, by contrast, that cooperative arrangements are easier to monitor and enforce in concentrated markets.

It is also possible that this relationship between rejection of the null hypothesis and market concentration is indicative of an information based model of hospital competition. Satterthwaite (1979) introduces such a model in which reductions in concentration lead to less competition in a market for "reputation" goods.[9] This unexpected result occurs because as competition increases, search becomes more costly for consumers. In response to the increased cost, consumers investigate fewer firms, so that competition actually decreases.

[8] The difference between these concentration levels, however, is statistically insignificant.

[9] For a reputation good, products are differentiated and quality is consumer specific. Furthermore, consumers can only evaluate quality over time [Satterthwaite (1979)].

Table 5.6 summarizes the chi-squared statistics testing for Cournot behavior by county and position on the urban/rural continuum as Chapter Four defines it. This table reads as follows: Moving across the first row, fifteen hospitals, or 8.11 percent of the hospitals in the sample, are located in Broward county. I reject H_0: $\alpha = 0$ for eleven or 73.33 percent of the hospitals in this county and cannot reject this hypothesis for the remaining four or 26.67 percent of Broward county hospitals. The "Area Total" for counties with an urban/rural indicator of zero illustrates that 82 or 44.32 percent of the hospitals in the sample have this classification. I reject H_0: $\alpha = 0$ for 65 or 79.27 percent of these hospitals, but I cannot reject this hypothesis for the remaining seventeen or 20.73 percent of hospitals in this category.

Table 5.6 shows that, for all but classification "seven" on the urban/rural continuum, the majority of hospitals in each area depart from Cournot behavior. A county-level analysis is somewhat more informative. The third column of Table 5.6 shows that the ten counties containing the most hospitals account for 109 or 58.92 percent of the hospitals in the sample.[10] Notice that the percentage of hospitals for which I can reject the null hypothesis of $\alpha = 0$ varies by county. I reject the null hypothesis, for example, for 93.75 percent of the hospitals in Pinellas county and for 81.82 percent of the hospitals in Hillsborough county. For hospitals located in Dade, Orange, and Volusia counties, by contrast, I can reject the null hypothesis for only 68, 66.67, and 66.67 percent of the hospitals, respectively.

[10] These counties are Broward, Dade, Hillsborough, Orange, Pasco, Pinellas, Duval, Palm Beach, Polk, and Volusia.

Table 5.6A contains descriptive statistics for these five counties (Dade, Orange, Volusia, Pinnelas, Hillsborough) to find out if they have similar demographics in spite of differences in hospital behavior. Table 5.6A also supports the pattern concerning hospital concentration that Table 5.5 identifies. The average Herfindahl index in both Pinellas and Hillsborough counties is substantially lower than the average Herfindahl index in Orange and Volusia counties. Recall from Table 5.6 that both Pinellas and Hillsborough counties have more hospitals for which I reject the hypothesis of Cournot behavior than does either Orange or Volusia counties. Unlike the Herfindahl index, the county elderly population and per capita income do not seem to differ systematically according to hospital behavior.

In addition to Cournot behavior, I also consider the possibility that Florida hospitals collude. Recall that an estimated conjectural elasticity that is not significantly different from one is evidence in support of the collusion hypothesis. The null hypothesis, therefore, becomes $\alpha = 1$ against the alternative $\alpha \neq 1$. Table 5.7 summarizes the results of the chi-squared tests for collusion as equation (3.10) illustrates. The structure of Table 5.7 follows that of Table 5.5

From Table 5.7, column three, I can reject collusive behavior at the five percent significance level for only 38 or 20.54 percent of hospitals in the sample. The average Herfindahl for this group of hospitals is 2284, which is significantly less ($p < .05$) than 2856, the average Herfindahl index for hospitals for which I cannot reject the null hypothesis that $\alpha = 1$. This result indicates that market concentration facilitates collusion and is consistent with the structure-conduct-performance school. This relationship

between market concentration and behavior contrasts with the pattern that Table 5.5 identifies in which hospitals that do not hold Cournot conjectures have less concentrated markets.

Table 5.7 also illustrates that hospitals for which I cannot reject the null hypothesis that $\alpha = 1$ are smaller (244 versus 263 beds) and are more likely to be located in rural areas (16.33 percent versus 5.26 percent) than are those hospitals for which I can reject the null hypothesis. This result may indicate that small rural hospitals need to act cooperatively to survive in a managed care environment.

Because the chi-squared statistics in equations (3.9) and (3.10) only identify departure from Cournot behavior or collusion, respectively, I estimate probit models to identify the factors that influence hospital behavior. I now discuss the specification of these models and the associated results.

B. Probit Estimation

(i) Specification

I use equation (5.1) to model hospital behavior:

$$y^*_i = \beta_0 + \sum_{j=1}^{k} \beta_j x_{ij} + u_i \qquad (i = 1, \ldots, 185), \qquad (5.1)$$

where y^*_i represents a hospital's unobservable expectation of competitor behavior. The results of the significance tests from equations (3.9) and (3.10) provide a proxy for the hospital's expectation. I denote the proxy by y_i. To identify the factors that contribute to cooperative behavior I estimate two specifications of equation (5.1) which differ according to the construction of the dependent variable:

$$\text{(a)} \qquad y_i = \begin{cases} 1 \text{ if } \alpha_i = 0 \text{ is rejected} \\ 0 \text{ otherwise} \end{cases}, (i = 1, \ldots, 185), \tag{5.2a}$$

and

$$\text{(b)} \qquad y_i = \begin{cases} 1 \text{ if } \alpha_i = 1 \text{ cannot be rejected} \\ 0 \text{ otherwise} \end{cases}, (i = 1, \ldots, 185). \tag{5.2b}$$

Equation (5.2a), therefore, identifies hospitals that depart from Cournot behavior, while equation (5.2b) identifies collusion. The regressors in equation (5.1), the x_{ij}, include three market structure variables AMSAVG, AVGAHHI, and MARKDOM, as well as BIG and LOCATION, as Table 5.1 defines them. I assume that the regression errors, u_i, have a zero mean and variance σ^2_i.

Table 5.8 contains the estimation results from equation (5.1), with the dependent variable as equation (5.2a) describes, while Table 5.9 contain the estimation results with the dependent variable as in equation (5.2b). Columns one through three of these tables contain three versions that differ according to the included regressors. The first version considers only the effect of hospital market share (AMSAVG) on behavior while the second focuses on how market structure (AVGAHHI, MARKDOM) affects behavior. The third version expands on the first by including hospital size (BIG) and location (LOCATION) as regressors.

(ii) Cournot Behavior

Table 5.8 presents the results from estimation of equation (5.1), with the dependent variable as in equation (5.2a). Using the results of tests for homoskedasticity,

I correct the covariance matrix for heteroskedasticity, conditional on the regressors for all versions in Table 5.8.

Overall, the results in Table 5.8 do not support the collusion hypothesis, because the coefficients on AVGAHHI and MARKDOM are negative. First, a positive, rather than a negative, relationship between the departure from Cournot behavior and market structure, as the Herfindahl index measures it, would provide evidence of collusive behavior [Clarke, *et al.* (1984)]. That is, a concentrated market facilitates strategic interplay among hospitals. Second, if the presence of a dominant hospital increases the likelihood of cooperative behavior, the coefficient on MARKDOM would be positive rather than negative. A positive relationship would imply that cooperative behavior will benefit hospitals of all sizes.

The results in Table 5.8 imply that hospital market concentration does not drive the overall rejection of Cournot behavior from the chi-squared statistics of equation (3.9). Instead, because the Cournot model only considers price competition, the overall rejection of Cournot behavior may indicate that Florida hospitals compete primarily along quality dimensions. The existence of a large Medicare population in Florida supports this hypothesis. Hospitals do not negotiate Medicare reimbursement rates, because the Health Care Financing Association sets the prices that hospitals receive for treating Medicare patients. As long as this price exceeds the marginal cost that the hospital incurs for treating Medicare patients, hospitals will compete for these patients. Quality, however, is the only dimension on which hospitals can compete for these patients. Price

competition may become more important in Florida hospital markets, though, as Medicare managed care networks become more prevalent.

(iii) Collusion

Table 5.9 present the results from estimation of equation (5.1), with the dependent variable as in equation (5.2b). The three columns in Table 5.9 are identical to those in Table 5.8. Using the results of tests for homoskedasticity, I correct the covariance matrix for heteroskedasticity, conditional on the regressors in versions (1) and (3), but not in (2).

The results in Table 5.9 strongly support the efficiency hypothesis. Contrary to the structure-conduct-performance paradigm, the coefficient on the Herfindahl index in version (2) is significantly negative, indicating that collusion is less likely in more concentrated markets. The significant negative coefficients on AMSAVG and BIG in version (3), moreover, imply that size, measured by either inpatient days or number of beds, does not increase the likelihood of collusion.[11]

Hospital location, by contrast, appears to be more important then either market structure or size in contributing to the likelihood of collusion. The positive coefficient on LOCATION indicates that rural hospitals are more likely to collude, as lower values of this variable identify urban areas. The negative coefficient on BIG, moreover, implies that smaller hospitals are more likely to collude. These results suggests, consistent with

[11] When BIG identifies hospitals with more than 400 beds in version (3), the coefficient on this variable remains negative but is significant at only the 10 percent level. The sign and significance of LOCATION and AMSAVG are unchanged.

those in Table 5.7, that cooperative behavior may be necessary for rural hospitals to survive under managed care.

C. A Possible Alternative Explanation

The results thus far imply that market structure does not have the expected effect on hospital behavior. Specifically, Table 5.5 illustrates that hospitals that do not hold the Cournot conjecture operate in less concentrated markets then do those hospitals that act as if they believe that their rivals do not react to their output choice. The probit regressions in Table 5.9 show, moreover, that collusion is less likely to occur in more concentrated markets . Because of this unconventional relationship between hospital behavior and market structure, I also consider the intermediate position, that hospitals engage in a Stackelberg leader-follower pattern of behavior. A finding that larger hospitals, measured in terms of either bed size or market share, are more likely to depart from Cournot behavior would be indicative of a Stackelberg leader-follower relationship. From Table 5.8, the positive, significant coefficient on AMSAVG supports this hypothesis.

To analyze further the relationship between hospital behavior and relative market position, I identify the top two hospitals in each market by market share. Not surprisingly, a small core of hospitals dominates in each market. Overall, 53 hospitals, (28.65 percent) have dominant positions. For 88.68 percent (47) of these hospitals, I can reject Cournot behavior. This relationship between market dominance and departure from Cournot behavior also supports a Stackelberg leader-follower market structure.

The results in this sub-section provide some preliminary evidence in support of a Stackelberg leader-follower market structure. Future research will involve formal modeling and testing of this more complex market structure. At this point I can only state the welfare implications of a Stackelberg solution. Comparing the Cournot, collusion, and Stackelberg equilibriums, we find that consumer surplus is larger in a Stackelberg leader-follower market structure than in either a Cournot or collusive situation. Even if the dominant hospitals in a market were to act cooperatively, the competitive fringe firms will limit their behavior. Specifically, the resulting dominant hospital price cannot exceed the costs of the more competitive fringe firms [Martin (1988b), Demsetz (1974)].

D. Price Function Analysis

Table 5.7 indicates that hospitals act cooperatively concerning capacity decisions. It is important to find out, however, if their behavior enables them to receive higher prices. To ascertain the effects that hospital behavior and market structure have on hospital prices, I estimate a price equation.[12] The relationship between hospital market structure and price may differ depending on whether price or quantity competition is more prevalent among Florida hospitals [Noether (1988)]. If hospitals compete primarily on quality, for example, prices should be lower in more concentrated markets. The most recent studies on the relationship between hospital prices and market structure find that

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[12] The dependent variable in this equation is the net price of the hospital market basket.

hospital prices are higher in more concentrated markets, consistent with the structure-conduct performance paradigm [Staten, *et al.* (1988), Melnick, *et al.* (1992)].

(i) Specification

Express the net price of the market basket of services that hospital i offers at time t, $price_{i,t}$, as a function of a vector of provider characteristics (X), a vector of market structure variables (Y), and hospital behavior measures (Z):

$$price_{i,t} = \beta_0 + \underline{\beta}_X X_{i,t} + \underline{\beta}_Y Y_{i,t} + \beta_Z Z_i + u_{i,t}. \qquad (5.3)$$

$i = 1,\ldots,184$[13]
$t = 1990,\ldots,1993$

Provider characteristics include ownership (PROFIT, NOPROFIT), teaching status (TEACH), the occupancy rate (HOCCUP), and patient-mix variables (KSHARE, MCARESH, MCAIDSH), as well as controls for product differences. A case-mix index (CASE) and the number of technologically advanced services that a hospital offers (HITECH) measure the extent of product differentiation among hospitals.

The market structure variables include market share (ADJMS) and the Herfindahl index (ADJHHI). I also use a dummy variable to identify hospitals sharing a market with a dominant hospital (MARKDOM), to ascertain whether the presence of a dominant hospital raises the prices that all other hospitals in the market receive.

ASIGN and ASIGN1 are dummy variables describing hospital behavior. The λ^2 statistics in equations (3.9) and (3.10) provide the basis for these two variables that identify cooperative behavior. Specifically, ASIGN takes a value of one if the test

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[13] Because one hospital has missing data on teaching status, I use data on 184 hospitals to estimate equation (5.3).

statistic in equation (3.9) indicates that the hospital's conjectural elasticity is significantly greater than zero. Similarly, ASIGN1 equals one if the test statistic in equation (3.10) indicates that the hospital's conjectural elasticity is not significantly different from one. I assume that the regression errors, $u_{i,t}$, have a zero mean and variance σ^2_i.

(ii) Results

Here I present and discuss the estimates of equation (5.3) which center around the effect of market structure on price and the extent of price competition in Florida hospital markets. Table 5.10 presents the estimates of equation (5.3). As Table 5.10 illustrates I estimate various versions of equation (5.3). Versions (1) and (2) differ only in their market structure variable. Version (1) uses market share while version (2) uses the Herfindahl index. The variations of equation (5.3) in columns (3) and (4) consider the effect of hospital behavior (ASIGN and ASIGN1) and the presence of a dominant hospital in the market (MARKDOM) on price.

Hausman tests [Hausman and Taylor (1981)] indicate that random effects estimation is appropriate for the price analysis.[14] This method can accommodate time invariant variables such as ownership and teaching status as regressors. Random effects estimation also improves the efficiency of the estimates because it uses both within-hospital variation and between-hospital variation, whereas fixed effects estimation uses only within-hospital variation.

[14] The Hausman test statistic is .0001 with an associated p-value of .9999. I cannot reject the null hypothesis that there is no correlation between the regressors and the error term. Under this scenario the random effects estimator is consistent and efficient.

(a) Effects of Market Structure and Price Competition

Market Structure

Overall, the results from the price regressions provide convincing evidence against the structure-conduct-performance paradigm, which predicts that prices will be higher in more concentrated markets. The coefficient on the Herfindahl index (ADJHHI) in column (2) is negative and insignificant as is the coefficient on MARKDOM in columns (3) and (4). The insignificance of MARKDOM indicates that the presence of a dominant hospital in a market does not create an umbrella under which other competing hospitals in that market can earn economic rent by charging higher prices. Instead, the negative, significant coefficient on ADJMS in columns (1) and (3) in Table 5.10 indicates that large market share hospitals actually receive lower prices.

The negative coefficient on ADJMS has two possible interpretations. First, high market share hospitals may agree to lower prices in managed care contracts in exchange for increased volume from these payors. Second, hospitals with large market shares may have lower costs do than smaller hospitals, consistent with the Demsetz hypothesis. The negative coefficient on ADJMS could indicate, therefore, that efficient hospitals pass on their cost savings to third party payors.

The insignificance of ASIGN and ASIGN1 in columns (3) and (4), moreover, implies that cooperative behavior does not enable a hospital to charge higher prices. The insignificance of these behavior variables indicates that third-party payors have a stronger bargaining position than do hospitals in managed care contract negotiations. In sum, the relative magnitude of the estimated coefficient on CASE implies that a hospital's case

mix index, rather than the market structure variables, is the most important determinant of a hospital's net price.

Price Competition

Theoretically, increased penetration of managed care networks should increase price competition among hospitals and lower hospital costs as hospitals compete for selection into these networks. Hospitals with a high percentage of managed care patients thus should accept lower prices. The insignificance of KSHARE, the percentage of managed care patients, in the price equations implies that price competition has not completely replaced quality competition in Florida hospital markets.

The insignificance of KSHARE may reflect the patient mix in Florida hospitals. Medicare covers on average, approximately one-half of each hospital's patient base. The Health Care Financing Association sets the prices that a hospital receives for treating these patients. Because of the large Medicare base, Florida hospitals may depend less than do other hospitals on managed care contracts, and therefore they may be less likely to grant large discounts to secure these contracts. The importance of price competition in Florida hospital markets may increase as Medicare HMOs continue to form.[15] Price competition may not lower payer costs significantly in Florida, however, because increased demand from an expanding Medicare population has the potential to fill hospital excess capacity [Murray and Anderson (1996)]. Hospitals with high occupancy rates that operate in markets with little excess capacity receive higher prices [Melnick, *et al.* (1992)].

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[15] See Murray and Anderson (1996) for a description of the various kinds of Medicare HMOs.

The insignificance of MCARESH, the percentage of Medicare patients, however, contradicts the predictions of the market segmentation model in Figure 6.1A of Chapter Six. According to this model the large Medicare base for Florida hospitals reduces demand elasticity and results in a higher price charged to the non-Medicare community. Following this line of reasoning, the estimated coefficient on MCARESH in equation (5.3) should be positive. The insignificance of MCARESH, however, may be a result of two offsetting effects. If hospitals with a large percentage of Medicare patients reduce the quality (or quantity) of services to remain solvent under Medicare's prospective payment system, their prices may reflect this lower quality. In spite of the lower quality, these hospitals may not grant large discounts in managed care contracts because of their large Medicare patient base.

IV. Summary and Policy Implications

Florida hospitals appear to engage in some cooperative behavior, given that I can reject the null hypothesis that $\alpha = 1$ for only 38 or 20.54 percent of the hospitals in the sample. It is plausible, however, that this result does not reflect explicit collusion to restrict output below the competitive level. Instead, this result may document the hospitals' similar responses to the incentives that exist because of the influence of managed care contracts and Medicare PPS. The cost-containment efforts of these private and public payors focus on reducing inpatient utilization. This decline in utilization resulted in hospital excess capacity. Advances in medical technology that enable hospitals to provide certain procedures, historically requiring inpatient care, on an

outpatient basis also increased the excess capacity in hospital markets [Magleby (1996)].[16]

Hospitals can choose among several alternatives to reduce their excess capacity. The most obvious solution is to merge. Federal hospital merger policy, however, is not well-defined and responding to an investigation and any ensuing litigation will be expensive [*Ibid.*]. Indeed, many legal commentators "argue that the prospect of litigation and the current state of the law give rise to a level of uncertainty that prevents procompetitive and efficient mergers that are necessary to the survival of the hospital industry" [*Ibid.* at 143]. Because of this uncertainty, hospitals also may engage in joint ventures as a means of reducing the under-utilization of expensive equipment [*Ibid.* at 181]. Joint ventures also allow hospitals to retain their autonomy and reduce managerial conflicts [Campbell (1996)].

The results of the significance tests from equation (3.10) thus may reflect an increase in joint venture activity among Florida hospitals and not explicit collusion to restrict output. Indeed, agreements to restrict output below the competitive level in an industry with excess capacity are unlikely. Instead, a conjectural elasticity that is not significantly different from one most likely reflects increased joint venture activity among Florida hospitals to reduce both excess capacity and operating expenses.

Recent Florida hospital merger decisions and Florida legislative changes support this hypothesis. In 1994, both the Department of Justice and the Florida attorney general challenged the proposed merger of the Mease Health System and Morton Plant Health

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[16] Magleby (1996), Section II(A), briefly reviews the incentives in the hospital industry that resulted in excess capacity.

Systems.[17] These hospitals had a combined market share of sixty percent and were the two largest hospitals in their market. The case settled when the plaintiffs allowed the two hospitals to form a joint venture partnership for both expensive services and those for which the patient is willing to travel.[18]

Florida is also one of the eighteen states that have passed hospital cooperation acts.[19] This state legislation provides immunity from antitrust prosecution for approved types of hospital cooperative behavior. To obtain immunity from antitrust prosecution Florida hospitals must explicitly describe the proposed behavior and show that it is "likely" that resulting efficiencies will outweigh any anti-competitive effect. Because this is a relatively low burden of proof, the act has probably increased joint venture activity among Florida hospitals.[20]

The results of the probit analysis in Table 5.9 also indicate that the results of the significance tests in equation (3.10) reflect cooperative behavior, such as joint ventures, rather than explicit collusion to restrict output. Recall that Table 5.9 illustrates that market structure does not have the expected effect on behavior. Indeed, high market concentration actually reduces the likelihood of collusion. Small rural hospitals, by

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[17] United States and State of Florida v. Morton Plant Health Systems, Inc. and Trustees of Mease Hospital, Inc., No. 94-748-CIV-T-23E M.D. Fla., filed May 5, 1994. See Magleby (1996) for a critique of the decision in this case.

[18] These services include open heart surgery, robotically assisted prosthetic implantation, neonatal level III services and diagnostic and therapeutic radiology services such as CAT scans, MRIs, and X-rays.

[19] See Magleby (1996) for a more detailed analysis of the various state cooperation acts.

[20] Other states impose a stricter burden of proof on applicant hospitals. Hospitals in Maine, Idaho, Nebraska, North Carolina, North Dakota, and Tennessee, for example, must show that efficiency gains outweigh any anti-competitive effects by "clear and convincing evidence." See Magleby (1996), footnote 266 at 192-193.

contrast, are most likely to collude, implying that cooperative behavior is necessary for these hospitals to survive on a managed care environment. Joint ventures are often a more feasible option than is a merger for rural hospitals to reduce costs and capacity [Campbell (1996)].

More important, even if hospitals act cooperatively concerning capacity decisions, their behavior has no impact on the price they receive because the coefficients on both ASIGN and ASIGN1, the variables identifying cooperative behavior in Table 5.10, are insignificant. The insignificance of these variables implies that in managed care contract negotiations, insurers currently enjoy more bargaining power than do Florida hospitals. Consistent with this finding, Zwanziger, *et al.* (1994) state that payor bargaining power is a function of the excess capacity in a hospital's market. Recall that the average occupancy rate for hospitals in this sample is approximately fifty percent.

Because hospital behavior has no impact on the price the hospital receives, both federal and state antitrust authorities should allow Florida hospitals to continue to reduce their excess capacity through merger and joint venture. Protection from federal antitrust prosecution under the Florida Hospital Cooperation Act should facilitate this effort.

Reduction of this excess capacity, furthermore, will not necessarily erode a payor's bargaining position. Recall that estimates of equation (5.3) reveal that hospital behavior does not influence the price that hospitals receive. Some health economists, moreover, argue that as few as two competing hospitals are sufficient to maintain competition in a market [Burda (1996)].[21] Indeed, payors "prefer to deal with two

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[21] In this article, the author is interviewing Monica Noether, a health economist.

strong, efficient provider[s] ... rather than four weak, inefficient ones."[22] Even if hospitals enjoyed a superior bargaining position in managed care negotiations, moreover, any price effects that impose benefits or costs on the actual purchasers of health insurance depend on the extent of competition among health insurance plans. From this perspective, the outcome of the bargaining game between the third-party payor and the hospital represents a redistribution of profit between upstream and downstream suppliers.[23]

Reduction in excess capacity will result in more concentrated Florida hospital markets. This additional concentration will allow Florida hospitals to minimize costly non-price competition. Because Florida hospitals have a large Medicare base, they currently engage primarily in non-price competition. Recall that earlier research on hospital competition shows that, under non-price competition, hospitals in less concentrated markets have higher costs than do those in more concentrated markets [Robinson and Luft (1985, 1987, 1988), Noether (1988)].

Although the formation of Medicare HMOs may increase the importance of price competition among Florida hospitals, the reduction in excess hospital capacity should not prevent the Health Care Financing Association (HCFA) from lowering its cost of providing health insurance to an expanding Medicare population. First, as I state earlier in this section, hospital behavior does not have an effect on the price that the hospital

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[22] Burda (1996) quoting Monica Noether.

[23] In this scenario the third-party payor supplies the insured with the product "insured medical care." The third-party payor then contracts with both physicians and hospitals. The obvious exception is an HMO that both owns its own hospital and actually employs physicians.

receives. More important, in the most common kind of Medicare HMO, a risk-based model, the outcome of the bargaining game between the hospital and the supplier will be solely a redistribution of profit, because the reimbursement that the HMO receives from HCFA is a non-negotiable, capitated amount equal to the average per-capita cost that Medicare pays in the pertinent geographic area.[24] In sum, continued reduction in capacity through both merger and joint venture will result in an efficient structure for the hospital industry in Florida.

[24] Murray and Anderson (1996) provide a description of the various types of Medicare HMOs.

V. Tables

A. Table 5.1

Variable definitions

Variable	Definition
ADJHHI	The Herfindahl index adjusted for the common ownership in multi-hospital systems.
ADJMS	Hospital market share adjusted for the common ownership in multi-hospital systems.
ASIGN	A dummy variable equal to one for hospitals with conjectural elasticities significantly different from zero.
ASIGN1	A dummy variable equal to one for hospitals with conjectural elasticities not significantly different from one.
AMSAVG	A hospital's average market share over the sample period, adjusted for common ownership. This variable is a regressor in the probit analysis.
AVGAHHI	A hospital's average Herfindahl index over the sample period, adjusted for common ownership. This variable is a regressor in the probit analysis.
BEDS	Hospital bed size.
BIG	A dummy variable equal to one for hospitals with more than 250 beds.
CAPINTEN	Hospital capital intensity.
CASE	The hospital's annual case-mix score.
DUM91, DUM92, DUM93	Dummy variables indicating 1991, 1992, and 1993 respectively.
HHI	The Herfindahl index.
HITECH	The number of technologically advanced services that the hospital offers.
HOCCUP	The hospital's occupancy rate.

Table 5.1, continued

Variable	Definition
KSHARE	The percentage of PPO and HMO patients.
LOCATION	The Department of Agriculture's urban-rural continuum. Lower values of this continuum identify urban areas.
MARKDOM	A dummy variable equal to one for hospitals in a market with a dominant hospital.
MCAIDSH	The percentage of Medicaid patients.
MCARESH	The percentage of Medicare patients.
MS	Hospital market share measured in privately insured inpatient days.
NMARGIN	The net margin earned on the market basket of hospital services.
NPRMCARE, NPRMCAID	The Medicare and Medicaid percentages of non-profit hospitals, respectively.
NTPRICE	The price, net of contractual allowances, for the market basket of hospital services.
POCCUP, NPOCCUP	The occupancy rates of for-profit and non-profit hospitals, respectively.
PRMCARE, PRMCAID	The Medicare and Medicaid percentages of for-profit hospitals, respectively.
PROFIT, NOPROFIT	Dummy variables representing for-profit and non-profit hospitals, respectively. Government hospitals are the omitted category.
TEACH	A dummy variable equal to one identifying teaching hospitals.
UNTCOST	The average variable cost of the market basket of hospital services.
URBAN	A dummy variable equal to one for hospitals located in urban areas as the Department of Agriculture's urban-rural continuum defines them.

B. Table 5.2

Descriptive statistics, by year, Florida hospitals, 1990 and 1993

	1990		1993	
Variable	Mean	Standard deviation	Mean	Standard deviation
NMARGIN	.2846	.2116	.3067	.1880
NTPRICE	903.61	224.08	988.42	276.52
UNTCOST	617.84	142.48	659.21	172.92
HHI	2539.8	1546.3	2756.2	1861.5
ADJHHI	2683.8	1556.3	2800.9	1884.6
MS	13.20	16.01	14.02	18.64
ADJMS	15.114	17.876	15.13	19.68
HOCCUP	52.50	16.01	49.72	15.76
HITECH	1.54	1.91	1.86	1.87
CASE	1.16	.1764	1.23	.1917
CAPINTEN	7.31	3.62	109.39	171.95
LOCATION	1.70	2.04	1.70	2.04
BEDS	247.57	203.28	247.57	203.28
MARKDOM	.2270	.4201	.2865	.4534
MCAIDSH	7.44	7.35	9.94	7.87
MCARESH	54.30	15.95	57.91	16.68
KSHARE	9.56	7.90	11.91	8.06
PROFIT	.4487	.4987	.4595	.4997
NOPROFIT	.4270	.4960	.4270	.4960
GOVT	.1243	.3309	.1135	.3181
TEACH	.1250	.3316	.1196	.3253

C. Table 5.3

Fixed Effects Estimates: Equation (3.6)
Dependent Variable: Net Margin

Regressors ↓	Estimated Coefficient	t-ratio (p-value)
Case	-.0277	-.245 (.8068)
Hitech	-.0110	-.887 (.3759)
Hoccup	.0017	.401 (.6887)
Capinten	-.0001	-1.352 (.1772)
Kshare	.0067***	3.622 (.0003)
Mcaresh	-.0044	-.911 (.3632)
Mcaidsh	.0025	.258 (.7962)
Poccup	-.0012	-.256 (.7982)
Npoccup	-.0012	-.274 (.7844)
Prmcare	.0034	.666 (.5055)
Nprmcare	.0037	.735 (.4630)
Prmcaid	-.0046	-.448 (.6546)
Nprmcaid	-.0088	-.843 (.3999)
DUM91	.0337*	1.795 (.0735)
DUM92	.0257	1.060 (.2900)
DUM93	.0509*	1.773 (.0772)
Diagnostics		
F statistic	13.714***	
Sample size	185	

Notes: I obtain these entries by applying the least squares method, with hospital-specific intercepts, hospital-specific market share variables, and no overall constant term, to equation (3.6). Notice that '*,' '**,' and '***,' indicate significance at the 10%, 5%, and 1% levels, respectively.

D. Table 5.4

Confidence Intervals for Selected Conjectural Elasticities

Estimated	**Coefficients**	Estimated	Standard	**Confidence**	**Interval for** $(\hat{\alpha})$
Intercept ($\beta_{0,i}$)	Market Share ($\beta_{1,i}$)	Conjectural Elasticity $(\hat{\alpha})$	Deviation $(\hat{\alpha})$	Upper Bound	Lower Bound
0.22416	0.116566	0.657889	0.539419	1.71515	-0.39937
0.434829	0.188659	0.697414	0.322151	1.328829	0.065998
0.414417	0.069438	0.85649	0.318333	1.480422	0.232558
0.174101	0.01927	0.900347	0.239437	1.369644	0.43105
0.239365	0.019434	0.924907	0.340171	1.591642	0.258172
0.170695	0.012421	0.932169	0.099468	1.127126	0.737211
0.408132	0.028036	0.935722	0.228522	1.383626	0.487818
0.520592	0.033307	0.939868	0.18222	1.297018	0.582718
0.26523	0.014965	0.946591	0.226875	1.391265	0.501916
0.138409	0.007718	0.947183	0.305751	1.546455	0.347911
0.157062	0.007854	0.952376	0.143511	1.233657	0.671094
0.315288	0.012458	0.961989	0.229917	1.412626	0.511352
0.331625	0.012566	0.963491	0.081115	1.122477	0.804505
0.120554	0.003966	0.96815	0.277789	1.512616	0.423683
0.328228	0.009709	0.97127	0.451069	1.855366	0.087174
0.261096	0.006431	0.975961	0.176306	1.321521	0.630402
0.23636	0.00535	0.977866	0.179438	1.329564	0.626168
0.134191	0.002745	0.979954	0.154772	1.283307	0.676602
0.427379	0.008565	0.980353	0.157067	1.288205	0.672501
0.533984	0.010208	0.981242	0.063773	1.106238	0.856246
0.181183	0.002643	0.985622	0.040184	1.064383	0.906861
0.121835	0.00163	0.986798	0.039725	1.064659	0.908937
0.260879	0.00307	0.988369	0.065963	1.117656	0.859082
0.493878	0.005701	0.988588	0.244606	1.468017	0.50916
0.143677	0.001569	0.989198	0.119162	1.222756	0.75564
0.147568	0.001569	0.989479	0.088191	1.162335	0.816624
0.15932	0.001673	0.989608	0.0677	1.122301	0.856916
0.248222	0.002416	0.990361	0.061497	1.110896	0.869826
0.262483	0.002363	0.991078	0.02953	1.048957	0.933199
0.441556	0.003841	0.991376	0.152472	1.290222	0.692531
0.353754	0.002204	0.993808	0.043801	1.079659	0.907958
0.463969	0.002843	0.99391	0.240039	1.464387	0.523433

Table 5.4 continued

Estimated	**Coefficients**	Estimated	Standard	**Confidence**	**Interval for** ($\hat{\alpha}$)
Intercept ($\beta_{0,1}$)	Market Share ($\beta_{1,i}$)	Conjectural Elasticity ($\hat{\alpha}$)	Deviation ($\hat{\alpha}$)	Upper Bound	Lower Bound
0.473268	0.001109	0.997662	0.004794	1.007058	0.988266
0.353001	0.000798	0.997744	0.006922	1.011311	0.984178
0.391158	0.000579	0.998522	0.013429	1.024842	0.972201
0.529588	0.000377	0.999289	0.087902	1.171576	0.827001
0.515176	0.000162	0.999686	0.065318	1.127709	0.871662
0.641931	-0.00032	1.000491	0.059731	1.117564	0.883418
0.490355	-0.00032	1.000647	0.002939	1.006408	0.994886
0.356893	-0.0004	1.001114	0.012313	1.025247	0.97698
0.699322	-0.00106	1.001524	0.021153	1.042983	0.960064
0.401926	-0.00068	1.0017	0.008206	1.017783	0.985616
0.524372	-0.00121	1.002307	0.088383	1.175537	0.829077
0.559292	-0.0014	1.002517	0.014077	1.030108	0.974925
0.357702	-0.00093	1.002601	0.086794	1.172717	0.832485
0.561705	-0.00224	1.004009	0.089186	1.178813	0.829205
0.492092	-0.00221	1.004513	0.084916	1.170949	0.838078
0.84431	-0.00511	1.006094	0.003701	1.013349	0.998839
0.339548	-0.00279	1.008285	0.051456	1.109138	0.907431
0.943678	-0.00843	1.009017	0.006655	1.02206	0.995974
0.317667	-0.00325	1.01034	0.071598	1.150671	0.870009
1.112504	-0.01263	1.011479	0.01934	1.049385	0.973574
1.302731	-0.01488	1.011556	0.033831	1.077865	0.945246
1.883894	-0.02168	1.01164	0.012232	1.035614	0.987666
0.915342	-0.01084	1.011979	0.009551	1.030699	0.993259
0.68219	-0.00846	1.012551	0.005473	1.023277	1.001825
1.255709	-0.01647	1.013292	0.003634	1.020415	1.006169
0.794477	-0.01079	1.013771	0.017394	1.047864	0.979678
0.527991	-0.00788	1.015156	0.030851	1.075624	0.954689
1.610228	-0.02533	1.015983	0.01462	1.044639	0.987327
0.735364	-0.01256	1.017373	0.017019	1.050729	0.984016
0.444339	-0.00768	1.01759	0.034327	1.084871	0.95031
0.589533	-0.01315	1.022808	0.014631	1.051484	0.994131
0.549594	-0.01242	1.023125	0.022745	1.067704	0.978546

Table 5.4 continued

Estimated Coefficients		Estimated	Standard	**Confidence Interval for** $(\hat{\alpha})$	
Intercept ($\beta_{0,i}$)	Market Share ($\beta_{1,i}$)	Conjectural Elasticity $(\hat{\alpha})$	Deviation $(\hat{\alpha})$	Upper Bound	Lower Bound
0.44385	-0.01094	1.025276	0.032743	1.089453	0.961099
0.426446	-0.0108	1.025971	0.242932	1.502119	0.549824
0.608259	-0.01607	1.02713	0.025068	1.076262	0.977997
0.469154	-0.01254	1.02747	0.034997	1.096065	0.958875
-2.43223	0.066589	1.028148	0.007278	1.042412	1.013884
-1.90063	0.053833	1.029149	0.012748	1.054135	1.004164
0.332463	-0.00949	1.029386	0.144831	1.313255	0.745518
0.635578	-0.01923	1.031195	0.019104	1.06864	0.99375
0.403141	-0.01249	1.03197	0.221236	1.465592	0.598347
0.486459	-0.01586	1.033691	0.317543	1.656074	0.411307
0.527185	-0.01772	1.034786	0.029855	1.093301	0.97627
1.669243	-0.0618	1.038449	0.009692	1.057445	1.019452
0.753068	-0.03057	1.042317	0.02698	1.095199	0.989436
0.324191	-0.01338	1.043032	0.428553	1.882995	0.203069
2.966068	-0.12354	1.043462	0.007473	1.05811	1.028815
0.687926	-0.02931	1.044504	0.054062	1.150466	0.938542
0.663014	-0.02867	1.045203	0.033757	1.111367	0.979039
1.061787	-0.0473	1.046627	0.015051	1.076126	1.017128
-0.44848	0.021593	1.050582	0.027019	1.10354	0.997625
0.563341	-0.02727	1.050862	0.121874	1.289736	0.811989
0.557701	-0.02821	1.053278	0.175123	1.396519	0.710036
0.700813	-0.0368	1.055427	0.179405	1.40706	0.703794
0.441402	-0.02358	1.056441	0.113406	1.278717	0.834164
1.049586	-0.05928	1.059859	0.023745	1.1064	1.013318
-0.16997	0.009708	1.060576	0.089607	1.236205	0.884946
0.11707	-0.00699	1.063451	0.121431	1.301456	0.825446
1.047533	-0.06275	1.06372	0.015434	1.09397	1.03347
2.367189	-0.1571	1.071085	0.007162	1.085122	1.057047
0.59379	-0.04158	1.075294	0.123499	1.317351	0.833236
0.931277	-0.06705	1.077589	0.084064	1.242354	0.912823
0.909913	-0.06557	1.077661	0.044526	1.164932	0.990389
-0.21457	0.016018	1.080676	0.201928	1.476455	0.684898
0.646123	-0.04863	1.081396	0.033776	1.147597	1.015194

Table 5.4 continued

Estimated Coefficients		Estimated	Standard	**Confidence Interval for** ($\hat{\alpha}$)	
Intercept ($\beta_{0,i}$)	Market Share ($\beta_{1,i}$)	Conjectural Elasticity ($\hat{\alpha}$)	Deviation ($\hat{\alpha}$)	Upper Bound	Lower Bound
-0.26654	0.02041	1.082923	0.076306	1.232482	0.933364
0.63314	-0.04848	1.082926	0.090566	1.260434	0.905417
-0.26876	0.023229	1.094608	0.172033	1.431793	0.757423
-0.06473	0.005633	1.095324	0.287898	1.659605	0.531044
0.582069	-0.05269	1.099521	0.128511	1.351403	0.847639
-1.65822	0.15222	1.101076	0.017442	1.135262	1.066889
0.767922	-0.07279	1.104716	0.045906	1.194691	1.01474
1.006859	-0.09679	1.106357	0.030613	1.166358	1.046356
0.457781	-0.04719	1.114932	0.196105	1.499297	0.730567
0.234824	-0.02559	1.122276	0.138466	1.393671	0.850882
0.34506	-0.03779	1.122972	0.246216	1.605556	0.640388
-0.98329	0.109387	1.125171	0.085216	1.292195	0.958147
0.356389	-0.04001	1.126452	0.103815	1.329929	0.922974
0.911316	-0.10802	1.134467	0.032483	1.198134	1.0708
1.092541	-0.13333	1.138997	0.087863	1.31121	0.966785
-0.53183	0.065113	1.139513	0.081011	1.298294	0.980731
1.087203	-0.1485	1.158199	0.038388	1.233439	1.08296
-2.10016	0.288637	1.159334	0.016393	1.191464	1.127205
0.673928	-0.0953	1.164704	0.161038	1.480338	0.84907
1.203206	-0.17175	1.166517	0.057534	1.279283	1.053751
0.635426	-0.09402	1.173668	0.141245	1.450507	0.896828
0.571925	-0.0942	1.197185	0.088085	1.369831	1.024539
1.391709	-0.2421	1.210595	0.053044	1.314561	1.10663
0.818186	-0.14323	1.212206	0.087603	1.383908	1.040505
2.011616	-0.36625	1.222598	0.031036	1.283429	1.161767
-0.39259	0.073461	1.230194	0.157107	1.538123	0.922265
-0.53164	0.103475	1.241669	0.246148	1.724119	0.759218
0.829332	-0.2063	1.331127	0.208338	1.73947	0.922784
0.764861	-0.19087	1.332536	0.271158	1.864005	0.801067
-0.43225	0.109659	1.339929	0.230988	1.792665	0.887193
0.876854	-0.23258	1.360987	0.13318	1.62202	1.099954
-0.35909	0.09654	1.367703	0.184147	1.72863	1.006775
0.655601	-0.19155	1.412778	0.204828	1.814241	1.011315
-1.21581	0.359233	1.419382	0.104577	1.624353	1.21441

Notes: I obtain the intercept and market share coefficients from estimation of equation (3.6) and use them to compute $\hat{\alpha}$ according to equation (3.7). I then use a Taylor series expansion to calculate the standard deviation of $\hat{\alpha}$.

E. Table 5.5

Summary of significance tests for Cournot behavior, by selected characteristics: Florida hospitals, 1990-93

Descriptive characteristics ↓	**Complete Sample**	**Group I** H_o: $\alpha = 0$ rejected	**Group II** H_o: $\alpha = 0$ not rejected
Ownership			
For-profit	45.95 %	46.81 %	43.18 %
Non-profit	42.70 %	43.97 %	38.64 %
Government	11.35 %	9.22 %	18.18 %
	100.00 %	100.00 %	100.00 %
Geographic region			
Urban	85.95 %	88.65 %	77.27 %
Rural	14.05 %	11.35 %	22.73 %
	100.00 %	100.00 %	100.00 %
Mean Bed size	248	268	181
	(202.73)	(189.93)	(226.83)
Mean urban bed size	273	290	209
	(206.33)	(190.45)	(246.24)
Mean rural bed size	94	99.06	87
	(68.82)	(47.41)	(92.86)
Mean Herfindahl index: ADJHHI	2739	2723	2789
	(1586.23)	(1449.17)	(1961.12)
Mean urban ADJHHI	2678	2628	2861
	(1590.92)	(1421.68)	(2088.71)
Mean rural ADJHHI	3114	3471	2544
	(1503.61)	(1444.50)	(1418.35)
N	185	141	44

Notes: This table reads as follows: From column three, 46.81 percent of the hospitals for which I reject H_o: $\alpha = 0$ are for-profit hospitals. For comparative purposes, column two contains the descriptive characteristics for the entire sample. The numbers in parentheses below the various mean bed size and mean Herfindahl index entries are the respective standard deviations. The Herfindahl index reflects the common ownership of hospitals in multi-hospital systems.

F. Table 5.6

Categorization, by county, of significance tests for Cournot behavior: Florida hospitals, 1990-93

County ↓	Urban/ Rural Indicator ↓	Hospital Percentages ↓					
		Overall Sample		Group I: $\alpha = 0$ rejected		Group II: $\alpha = 0$ not rejected	
Broward	0	8.11 %	(15)	73.33 %	(11)	26.67 %	(4)
Dade	0	13.51	(25)	68.00	(17)	32.00	(8)
Hernando	0	1.08	(2)	100.00	(2)		
Hillsborough	0	5.95	(11)	81.82	(9)	18.18	(2)
Orange	0	3.24	(6)	66.67	(4)	33.33	(2)
Pasco	0	2.70	(5)	100.00	(5)		
Pinellas	0	8.65	(16)	93.75	(15)	6.25	(1)
Seminole	0	1.08	(2)	100.00	(2)		
Area Total		44.32 %	(82)	79.27 %	(65)	20.73 %	(17)
Lake	1	1.62 %	(3)	33.33 %	(1)	67.67 %	(2)
Osceola	1	1.62	(3)	67.67	(2)	33.33	(1)
Area Total		3.24 %	(6)	50.00 %	(3)	50.00 %	(3)
Clay	2	1.08 %	(2)	100.00 %	(1)		
Duval	2	3.78	(7)	100.00	(7)		
Escambia	2	1.62	(3)	100.00	(3)		
Flagler	2	.54	(1)	100.00	(1)		
Lee	2	2.16	(4)	75.00	(3)	25.00 %	(1)
Manatee	2	1.08	(2)	100.00	(2)		
Martin	2	1.08	(2)	100.00	(1)		
Nassua	2	.54	(1)			100.00	(1)
Palm Beach	2	7.03	(13)	92.31	(12)	7.69	(1)
Polk	2	2.70	(5)	80.00	(4)	20.00	(1)
St. Johns	2	.54	(1)			100.00	(1)
St. Lucie	2	1.08	(2)	100.00	(2)		
Santa Rosa	2	1.62	(3)	33.33	(1)	67.67	(2)
Sarasota	2	2.16	(4)	75.00	(3)	25.00	(1)
Volusia	2	3.24	(6)	66.67	(4)	33.33	(2)
Area Total		30.27 %	(56)	82.14	(46)	17.86	(10)
Alachua	3	1.08 %	(2)	100.00 %	(2)		
Bay	3	1.08	(2)	100.00	(2)		
Charlotte	3	1.62	(3)	100.00	(3)		
Gadsen	3	.54	(1)			100.00 %	(1)
Leon	3	.54	(1)	100.00	(1)		
Marion	3	.54	(1)			100.00	(1)

Table 5.6 continued

County ↓	Urban/ Rural Indicator ↓	Hospital Percentages ↓		
		Overall Sample	Group I: $\alpha = 0$ rejected	Group II: $\alpha = 0$ not rejected
Taylor	3	.54 (1)	100.00 (1)	
Okaloosa	3	2.16 (4)	50.00 (2)	50.00 (2)
Area Total		8.11 % (15)	73.33 % (11)	26.67 % (4)
Citrus	4	1.08 % (2)	100.00 % (2)	
Indian River	4	1.08 (2)	50.00 (1)	50.00 % (1)
Monroe	4	1.62 (3)	33.33 (1)	67.67 (2)
Area Total		3.78 % (7)	57.14 % (4)	42.86 % (3)
Bradford	6	.54 % (1)		100.00 % (1)
Columbia	6	1.08 (2)	100.00 % (2)	
Desoto	6	.54 (1)	100.00 (1)	
Gulf	6	.54 (1)		100.00 (1)
Hendry	6	.54 (1)		100.00 (1)
Highlands	6	1.08 (2)	50.00 (1)	50.00 (1)
Jackson	6	1.08 (2)	100.00 (2)	
Okeechobee	6	.54 (1)	100.00 (1)	
Putnam	6	.54 (1)	100.00 (1)	
Washington	6	.54 (1)	100.00 (1)	
Area Total		7.03 % (13)	69.23 % (9)	30.77 % (4)
Franklin	7	.54 % (1)		100.00 % (1)
Holmes	7	.54 (1)		100.00 (1)
Suwannee	7	.54 (1)	100.00 % (1)	
Area Total		1.62 % (3)	33.33 % (1)	67.67 % (2)
Levy	8	.54 % (1)		100.00 % (1)
Union	8	.54 (1)	100.00 % (1)	
Area Total		1.08 % (2)	50.00 % (1)	50.00 % (1)
Hamilton	9	.54 % (1)	100.00 % (1)	
Number of hospitals		185	141	44

Notes: The figure in parentheses is the number of hospitals in each category. This table reads as follows: Fifteen hospitals or 8.11 percent of the hospitals in the sample are located in Broward county. I reject H_0: $\alpha = 0$ for eleven or 73.33 percent of these hospitals and cannot reject this hypothesis for the remaining four or 26.67 percent of these hospitals. Eighty- two or 44.32 percent of the hospitals in the sample have an urban/rural indicator of zero. I reject H_0: $\alpha = 0$ for 65 or 79.27 percent of these hospitals.

G. Table 5.6A

Characteristics of Florida Counties

County	Number of Hospitals	Percentage of population over 65 years of age (1990 Census)	1992 Per Capita Income	Average Herfindahl Index Over the Sample Period
Dade	50	13.9	17,340	962
Orange	15	11.3	19,138	3784
Volusia	8	22.7	16,706	4274
Pinellas	32	25.9	21,907	1806
Hillsborough	20	12.2	18,689	2234
State	377	18.2	19,797	2754

Notes: I select the counties in this table based on the analysis on Table 5.6. Pinellas and Hillsborough counties contain a large percentage of hospitals for which I reject H_0: $\alpha = 0$. Dade, Orange, and Voluia counties, by contrast, have a substantial number of hospitals for which I do not reject H_0: $\alpha = 0$. I obtain the data in columns two, three, and four from the 1994 Florida Statistical Abstract and calculate the entries in column five. Notice that the state entry in column five reflects the average Herfindahl (adjusted for common ownership) for all hospitals in the sample.

H. Table 5.7

Summary of significance tests for collusion, by selected characteristics: Florida hospitals, 1990-93

Descriptive characteristics ↓	**Complete Sample**	**Group I** H_o: $\alpha = 1$ rejected	**Group II** Ho: $\alpha = 1$ not rejected
Ownership			
For- profit	45.95 %	50.05 %	44.90 %
Non- profit	42.7 %	42.11 %	42.86 %
Government	11.35 %	7.84 %	12.24 %
	100.00 %	100.00 %	100.00 %
Geographic region			
Urban	85.95 %	94.74 %	83.67 %
Rural	14.05 %	5.26 %	16.33 %
	100.00 %	100.00 %	100.00 %
Mean bed size	248	263	244
	(202.73)	(256.32)	(186.18)
Mean urban bed size	273	275	272
	(206.33)	(257.87)	(188.60)
Mean rural bed size	94	43	99
	(68.82)	(15.5)	(69.78)
Mean Herfindahl Index: ADJHHI	2739	2284	2856
	(1586.23)	(1450.5)	(1598.57)
Mean urban ADJHHI	2678	2353	2772
	(1590.92)	(1459.47)	(1615.13)
Mean rural ADJHHI	3114	1040	3287
	(1503.61)	(9.44)	(1435.58)
N	185	38	147

Notes: This table reads as follows: From column three, 50.05 % of the hospitals for which I reject H_o: $\alpha = 1$ are for-profit hospitals. For comparative purposes, column two contains the descriptive statistics for the entire sample. The numbers in parentheses below the various mean bed size and mean Herfindahl index entries are the respective standard deviations. The Herfindahl index reflects the common ownership of hospitals in multi-hospital systems.

I. Table 5.8

Probit analysis of the significance of a hospital's conjectural elasticity: Cournot behavior

Regressors ↓	(1) Estimated Coefficient	t-ratio (p-value)	(2) Estimated Coefficient	t-ratio (p-value)	(3) Estimated Coefficient	t-ratio (p-value)
Constant	-.40913	-1.606 (.1082)	.4320***	2.987 (.0028)	-.2878	-.865 (.3869)
AMSAVG	.2410***	3.853 (.0001)			.2606***	2.781 (.0054)
AVGAHHI			-.59E-04***	-2.766 (.0057)		
MARKDOM			-.0595	-1.033 (.3016)		
LOCATION					-.0911	-1.024 (.3056)
BIG					-.1941	-.280 (.7796)
Diagnostics						
χ^2:statistic testing β=0 (p-value)	37.28*** (.00001)		10.52** (.0326)		38.95*** (.00001)	
χ^2 testing homoskedasticity (p-value)	29.43*** (.00001)		10.33*** (.0057)		26.91*** (.00001)	
Percentage of correct predictions	82.5%		78.69%		81.97%	

Notes: In these regressions the dependent variable equals one if the hospital's estimated conjectural elasticity is significantly greater than zero and equals zero otherwise. Using the results from tests for homoskedasticity, I correct the covariance matrix for heteroskedasticity, conditional on the regressors. Notice that '*,' '**,' and '***' indicate significance at the 10%, 5%, and 1% levels, respectively.

J. Table 5.9

Probit analysis of the significance of a hospital's conjectural elasticity: collusion

Regressors ↓	(1) Estimated Coefficient	(1) t-ratio (p-value)	(2) Estimated Coefficient	(2) t-ratio (p-value)	(3) Estimated Coefficient	(3) t-ratio (p-value)
Constant	-.5844***	-4.905 (.0000)	2.0089	1.570 (.1165)	-.6746***	-4.562 (.0000)
AMSAVG	-.0078	-.888 (.3743)			-.0177***	-.2.683 (.0073)
AVGAHHI			-.0028**	-2.053 (.0401)		
MARKDOM			.0063	.003 (.9979)		
LOCATION					.1130**	2.470 (.0135)
BIG					-.0930**	-2.005 (..0450)
Diagnostics						
χ^2:statistic testing β=0 (p-value)	3.271 (.1949)		12.082** (.0168)		14.469*** (.0023)	
χ^2 testing homoskedasticity (p-value)	3.14* (.0762)		5.99** (.05)		-------	
Percentage of correct predictions	76.22%		77.30%		77.84%	

Notes: In these regressions the dependent variable takes a value of one when I cannot reject the collusion hypothesis and zero otherwise. Using the results of tests for homoskedasticity, I correct the covariance matrix for heteroskedasticity, conditional on the regressors, in versions (1) and (3), but not in (2). Notice that '*,' '**,' and '***' indicate significance at the 10%, 5%, and 1% levels, respectively.

K. Table 5.10

Net price analysis, Florida hospitals: 1990-93
Equation (5.3)
Dependent Variable: Net Price (NTPRICE)

Regressors ↓	(1) Estimated Coefficient	(1) t-ratio (p-value)	(2) Estimated Coefficient	(2) t-ratio (p-value)
Constant	524.45***	4.853 (.0000)	545.07***	4.917 (.0000)
DUM91	29.72*	1.925 (.0542)	29.84*	1.928 (.0539)
DUM92	23.38	1.39 (.1662)	23.69	1.399 (.1619)
DUM93	64.25***	3.462 (.0005)	64.00***	3.44 (.0006)
PROFIT	3.87	.083 (.9337)	3.0757	.066 (.9474)
NOPROFIT	57.22	1.281 (.2003)	57.39	1.284 (.1992)
ADJMS	-1.128**	-1.991 (.0465)		
ADJHHI			-.0091	-1.513 (.1303)
KSHARE	.0481	.036 (.9717)	.0374	.027 (.9781)
MCAIDSH	.2504	.129 (.8977)	.5387	.277 (.7819)
MCARESH	-.8764	-.760 (.4471)	-.6320	-.551 (.5818)
URBAN	92.68*	1.957 (.0503)	90.79*	1.917 (.0552)
TEACH	-30.72	-.783 (.4338)	-31.65	-.803 (.4221)
CASE	264.64***	3.569 (.0004)	257.66***	3.466 (.0005)
HITECH	9.77	1.213 (.2252)	8.06	1.008 (.3137)
HOCCUP	.3662	.432 (.6657)	.0678	.081 (.9354)
Diagnostics				
Adjusted R^2	.1112		.1081	
F-ratio (p-value)	7.49*** (.0000)		7.28*** (.0000)	
LM statistic (p-value)	360.20*** (.0000)		358.43*** (.0000)	

Table 5.10 continued

Regressors ↓	(3) Estimated Coefficient	t-ratio (p-value)	(4) Estimated Coefficient	t-ratio (p-value)
Constant	528.40***	4.791 (.0000)	486.75***	4.400 (.0000)
DUM91	29.76*	1.94 (.0523)	30.47*	1.989 (.0467)
DUM92	24.01	1.426 (.1539)	25.65	1.523 (.1277)
DUM93	64.93***	3.507 (.0005)	67.07***	3.619 (.0003)
PROFIT	3.8344	.082 (.9349)	7..045	.151 (.8798)
NOPROFIT	57.83	1.286 (.1983)	59.30	1.329 (.1838)
ADJMS	-1.0942*	-1.913 (.0557)		
ADJHHI			-1.156**	-2.029 (.0425)
KSHARE	.0615	.045 (.9637)	.0419	.031 (.9752)
MCAIDSH	.2383	.122 (.9026)	-.0692	-.035 (.9717)
MCARESH	-.8735	-.758 (.4487)	-1.216	-1.038 (.2992)
URBAN	92.24*	1.942 (.0522)	100.32**	2.105 (.0353)
TEACH	-32.35	-.824 (.4102)	-30.89	-.789 (.4300)
CASE	264.49***	3.579 (.0003)	267.54***	3.627 (.0003)
HITECH	9.64	1.190 (.2342)	8.958	1.115 (.2647)
HOCCUP	.4020	.473 (.6359)	.4303	.509 (.6111)
ASIGN	-4.9345	-.137 (.8914)		
ASIGN1			58.86	1.529 (.1262)
MARKDOM	-9.1127	-.456 (.6481)	-10.434	-.523 (.6010)
Diagnostics				
Adjusted R^2	.1067		.1106	
F-ratio (p-value)	6.41*** (.0000)		6.78 (.0000)	
LM statistic (p-value)	356.15*** (.0000)		355.00*** (.0000)	

Notes: I estimate equation (5.3) using a random effects model. Breusch and Pagan's LM statistic tests the random effects model against the pooled OLS model without any group effects. Notice that '*,' '**,' and '***' indicate significance at the 10 %, 5%, and 1% levels, respectively.

CHAPTER SIX

Cross Section Estimation and Comparison With California Hospital Markets

I. Introduction

This chapter presents estimation results for a cross section version of equation (3.6), which illustrates the relationship between hospital margin and market share. Cross section estimation is necessary for this research to facilitate comparison with the existing studies of hospital competition in California, which do not use panel data. Such a comparison is important because most studies on hospital competition use California data. One should analyze data from additional states before formulating national policy rules concerning hospital mergers. This chapter concludes with a discussion of the differences in hospital competition in Florida and California.

II. Specification

The cross section version of equation (3.6) that I estimate in this section is:

$$\text{Margin}_i = \beta_0 + \beta_1 S_i + \beta_2\left(\frac{p^k K_i}{p_i q_i}\right) + \underline{\beta} Z_i + u_i, \quad (i = 1, \ldots, 185) \qquad (6.1)$$

with the variables as Chapter Three, Section IV describes and the subscript i identifying the ith hospital in the sample. Equation (6.1) ignores the intra-hospital variation in the data to facilitate comparison with existing studies on hospital competition in California.

III. Results

Table 6.1 provides short variable definitions.[1] I estimate various versions of equation (6.1), which contain several different groups of regressors. Tables 6.2 and 6.3 contain the estimates of all versions of equation (6.1). Table 6.2, in particular, contains the estimates of equation (6.1) both with and without the ownership interaction terms, as Chapters Two and Three describe them. In this table versions (3) and (4) contain the ownership interaction terms (POCCUP, NPOCCUP, NPRMCARE, PRMCARE, NPRMCAID, PRMCAID), while I omit these terms from versions (1) and (2).[2] Versions (1) and (3), in addition, use market share (ADJMS) to reflect market structure, while variants (2) and (4) use the Herfindahl index (ADJHHI) to facilitate comparison with studies on California hospital markets.

Table 6.3 includes the effects of the market share interaction terms on hospital net margins (MSK, MSTECH, MSCAP), as Chapter Two discusses.[3] I interact hospital

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[1] Section V contains all the tables pertinent to the analyses in this chapter.

[2] Ownership interaction terms are necessary because the fixed effects model that Chapter Five reports cannot have any time invariant variables, such as ownership status, as regressors. Because it is possible, however, that the estimated conjectural elasticities will vary systematically by hospital ownership status, ownership interaction variables incorporate hospital ownership into the fixed effects model. I use a Chow test in these cross section regressions to discern which coefficients differ according to ownership status.

Initially, I estimate a version of equation (6.1) in which I interacted all of the independent variables with the for-profit and non-profit dummy variables. I reject the hypothesis that all slope coefficients are the same regardless of ownership status ($F_{8,710} = 2.764$). In this regression the interaction terms on CASE, HITECH, CAPINTEN, ADJMS, and KSHARE are statistically insignificant. A Chow test ($F_{5,710} = .627$) indicates that the coefficients on this group of variables do not differ according to ownership. On the basis of these tests, I interact the for-profit and non-profit dummy variables (PROFIT, NOPROFIT) with the variables HOCCUP, MCARESH, and MCAIDSH.

[3] The positive market share coefficient may be a function of either scale economies or returns to technological innovation [Ravenscraft (1983)]. Alternatively, large market share hospitals, because of their importance in managed care networks, may have higher margins because of their superior bargaining position with insurers.

market share with a measure of capital intensity (MSCAP), the number of technologically advanced services that a hospital offers (MSTECH), and the percentage of managed care patients (MSK), respectively. The first version includes the market share interaction terms, while the second also incorporates the ownership interaction terms into the regression equation.[4] The analysis of the regression results centers around three main categories: the ownership interaction terms, the effect of market structure on net margins, and the impact of managed care on net margins.

Ownership Interaction Terms

Using the results from Table 6.2, column (3), the sum of the coefficients on NPRMCARE and MCARESH gives the total effect of a non-profit hospital's Medicare share on net margin. Similarly, the sum of the coefficients on NPRMCAID and MCAIDSH provides the effect of a non-profit hospital's Medicaid share on net margin. For non-profit hospitals a ten percent increase in the percentage of Medicaid patients results in a .013[5] percent increase in net margin. For Medicare patients the increase is .042 percent.[6] In addition, the occupancy rate appears not to affect non-profit hospital margins because the sum of the coefficients on HOCCUP and NPOCCUP is zero.

The positive effect that the share of Medicaid and Medicare patients has on non-profit hospital margins indicates that the courts' interpretation of the community benefit

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[4] For all variants of equation (6.1), the Breusch and Pagan Lagrange multiplier test rejects the assumption of homoskedasticity. As a result, I use White's estimator to obtain the corrected asymptotic standard errors.

[5] [.0086 + (-.0073)] * 10.

[6] [(.0083 + (-.0041)] * 10.

standard does not lead non-profit hospitals to depart from profit-maximizing behavior.[7] Recall from Chapter Two that a negative relationship between the Medicare and Medicaid shares and margins of non-profit hospitals indicates that the hospital is treating government insured patients beyond the profit maximizing quantity. Correspondingly, a negative relationship between the occupancy rate and margins of non-profit hospitals would be evidence that non-profit hospitals, to maintain their tax exempt status, treat in excess of the profit maximizing quantity of patients.[8]

Table 6.2, column (3), also illustrates that the effect of additional Medicare and Medicaid patients on for-profit hospital net margins is negligible. A ten percent increase in both Medicare and Medicaid patients causes net margin to change by only .033 percent[9] and -.004 percent,[10] respectively. The negative effect of Medicaid patients on margins in for-profit hospitals may indicate reimbursement rates below marginal cost for these hospitals. Alternatively, the negative coefficient for Medicaid patients also could

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[7] Recall from Chapter Two that courts now consider the amount of under-reimbursed care (Medicare and Medicaid) that a non-profit hospital provides when questioning the appropriateness of their tax-exempt status. Eisert (1995) finds that non-profit hospitals serve more Medicaid patients than do for-profit hospitals, and therefore she concludes that the community benefit standard affects the behavior of non-profit hospitals. This constraint becomes less important, however, as the number of for-profit hospitals in the market increases. In this sample about one-half of the hospitals are for-profits. The large presence of for-profit hospitals in this sample and the results in Table 6.2 provide evidence that for Florida non-profit hospitals, adherence to the community benefit standard does not cause deviation from profit-maximizing behavior.

[8] Chapter Two illustrates that in a market segmentation model, both non-profit and for-profit hospitals accept government insured patients when the marginal revenue from treating these patients exceeds the marginal revenue earned from treating privately insured patients. If non-profit hospitals must alter their behavior to comply with the community benefit standard, these hospitals will treat additional Medicare or Medicaid patients beyond the profit maximizing quantity. Because the marginal cost of treating these patients exceeds marginal revenue, margins will decline.

[9] $[.0083 + (-.0050)] * 10$

[10] $[.0086 + (-.0090)] * 10$.

indicate lower quality of for-profit hospitals that treat a high percentage of Medicaid patients.[11]

Market Structure

The positive significant coefficient on the Herfindahl index (ADJHHI) in columns two and four of Table 6.2 may reflect either the higher margins of more efficient large market share hospitals or the effects of collusion among hospitals in more concentrated markets. The magnitude of the market share coefficient (ADJMS) in columns one and three is substantially larger, however, than the estimated coefficient on ADJHHI, suggesting that market share may be more important than concentration in determining net margin. This relative importance of market share is consistent with the Demsetz hypothesis.

As Chapter Two discusses, the positive significant coefficient on ADJMS in Table 6.2 may reflect several effects. To discern the determinants of this positive market share coefficient, Table 6.3 reports the estimates of equation (6.1), including the market share interaction terms (MSK, MSTECH, MSCAP). Comparing columns (1) and (2), we notice that, except for MSK, which is insignificant, including the ownership interactions does not affect the sign or significance of the market share interaction coefficients.

Table 6.3 illustrates that the returns to technological innovation, as the positive, significant coefficient on MSTECH in both columns (1) and (2) indicates, best explains the positive relationship between hospital margins and market share. The negative

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[11] Eisert (1995) shows that higher quality hospitals will serve a smaller share of Medicaid patients.

coefficient on HITECH by itself, however, is indicative of costly non-price competition among hospitals. Providing technologically advanced services becomes profitable only as a hospital captures a greater share of the market, presumably because of the large fixed costs associated with provision of these services. Following this line of reasoning, the negative coefficient on MSCAP is surprising. It may reflect the effect of excess capacity.

Managed Care

From both Tables 6.2 and 6.3 we notice that the percentage of managed care patients that a hospital treats (KSHARE, and MSK, respectively) does not appear to affect margins, consistent with the analysis of the descriptive statistics in Chapter Five. This result may imply that managed care has not increased price competition among Florida hospitals. Alternatively, treating a high percentage of managed care patients may have two offsetting effects on a hospital's margins. Presumably, hospitals win network contracts partly because their efficiency allows them to charge lower prices. Price competition and a hospital's need for managed care contracts to fill excess capacity, however, may enable an insurer to capture some of the hospital's efficiency rent in the form of higher discounts, thereby reducing hospital margins. The large Medicare base in Florida implies that the lack of price competition among Florida hospitals probably best explains the insignificance of KSHARE and MSK. Growth in Medicare HMOs, however, may change this relationship.

In sum, it appears that market share is more important than the Herfindahl index in measuring hospital net margins in Florida. Although I obtain this result from cross-section regressions, it does support the efficiency hypothesis.

IV. Comparison with Studies of Hospital Competition in California

Hospital competition in Florida appears to be in a different state of development than current research finds is true of California hospital markets, implying that generalizing findings from studies on hospital competition in only one state will result in inefficient national policy rules. Table 6.4 compares both the summary statistics and the cross section results I obtain with the Florida data with those from studies of hospital competition in California markets.

Because the time period for this study is 1990-1993, while the studies on California hospital competition span 1983-1988, the difference in the regression results for the two states may be a function of different sample periods. There are also differences in the construction of the dependent variables. Real differences nevertheless may prevail in both hospital markets and in competition in Florida and California. Current data on managed care penetration, state demographics, and Medicare enrollees, also support the trends that the comparative analysis identifies. At a minimum, in spite of the difference in the sample periods, this comparative analysis illustrates that we need more studies on hospital competition using current multi-state data to evaluate alternative hospital merger policies.

Most important, market structure, as the Herfindahl index measures it, has less impact on hospital net margin and net price in Florida as compared to its impact in California. In Dranove, *et al.* (1993) the estimated coefficient on the Herfindahl index in the net margin equation ranges from .073 to .130, considerably higher than the estimates

I obtain, which average .23E-04.[12] Similarly, in Melnick, *et al.* (1992) the coefficient on the Herfindahl index in the net price equation ranges from .1021 to .1375, again considerably greater than the .0109 to -.1463 range of results from this study. Comparisons with California hospital markets on the effects of market share on net margin are not possible because neither Melnick, *et al.* (1992) nor Dranove, *et al.* (1993) report regressions that use market share rather the Herfindahl index as an independent variable.

Comparison of the descriptive statistics, revealing that Florida hospitals, on average, earn a higher net margin than do California hospitals, may indicate that the demand for hospital services in Florida is less elastic than is demand in California. Dranove, *et al.* (1993) find that the net margin[13] that hospitals earn by providing a basket of services is .045 in 1988. By contrast, in Florida the net margin in 1993 is .3067. A well-known relationship shows that the Lerner index increases as demand becomes less elastic:

$$\text{Lerner index} = \frac{1}{e_{Q,P}},$$

[12] The variation in the magnitude of the estimated coefficients on the Herfindahl index in the net margin equation between this study and Dranove, *et al.* (1993) may also result from differing market definitions. Dranove, *et al.* use geopolitical boundaries rather than patient discharge data to define hospital geographic markets. As Chapter Four points out, geographic markets based on discharge data are more economically meaningful.

[13] Dranove, *et al.* define net margin as (price - deductions from revenue- average variable cost)/price - deductions from revenue. The methodology they use to construct the net margin variable is identical to mine with the exception of the failure to exclude bad debt and charity care from contractual allowances when constructing net margin. Although the authors try to control for this omission by including the ratio of charity care and bad debt to net revenue as an independent variable, the statistically significant decrease in net margin over their sample period may be a result of increasing charity care and bad debt. The mean ratio of charity care and bad debt to net revenue increases from .037 in 1983 to .061 in 1988.

where $e_{Q,P}$ is the price elasticity of demand.[14]

The difference in the price elasticity of demand between the two states is likely the result of varying payor mixes, both government and private. Florida has a larger Medicare population than does California, and this population is increasing. Between 1990 and 1993 the mean percentage of Medicare patients in this sample increases from 54.3 to 57.91. In California, however, the mean percentage of Medicare patients in the Dranove sample declines from 46.7 in 1983 to 32.6 in 1988 [Dranove, *et al.* (1993)].

Current state level demographic statistics confirm trends that the Florida and California data samples identify. Florida has a larger elderly population than does California. In 1993 18.6 percent of the state's population was over 65 years of age as compared with only 10.6 percent in California [Statistical Abstract of the U.S. (1994)]. There are also more Medicare days of care in short-stay hospitals in Florida than in California. In 1993 there are 20.7 percent more days of care per 1,000 Medicare enrollees in Florida (2087 days) than in California (1656 days) [Health Care Financing Review, Statistical Supplement (1995)].

Eisert (1995) argues that market concentration also affects the slope of the privately insured population's demand curve. Specifically she states that, for all prices, the hospital's demand schedule for private pay patients is less elastic in more concentrated hospital markets. Florida hospital markets are more concentrated than are California hospital markets. For 1990 the average Herfindahl index for hospitals in this

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[14] The Lerner index is commonly expressed as (P-MC)/P. Assuming profit-maximizing behavior, MR equals MC. Making this substitution, the Lerner index becomes: $\{p-p[1-(1/e_{Q,P})]\}/p$, which simplifies to $1/e_{Q,P}$.

sample is 2684. The average Herfindahl index in California hospital markets in 1988, by contrast, is 2560 [Dranove, *et al.* (1993)].[15]

The degree of demand elasticity affects both the hospital's patient mix and the prices it charges to the privately insured population. Following Eisert (1995) the segmented market model in Figure 6.1 illustrates the effect of different demand elasticities, for a given Medicare reimbursement rate, on both a hospital's patient-mix and the price it charges to privately insured patients.[16]

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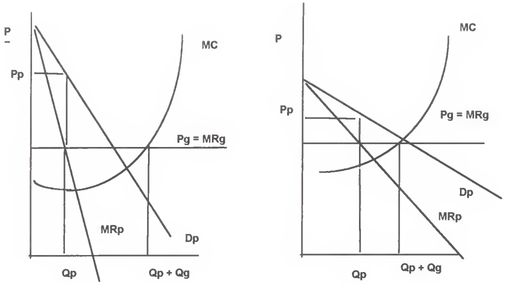
[15] The difference in concentration may be a result of varying market definitions. Dranove, *et al.* use geopolitical boundaries while I use patient discharge data to define geographic markets. I also adjust the Herfindahl index to reflect the effects of the common ownership in multi-hospital systems.

[16] For a detailed description on hospital pricing, see Morrisey (1994).

Figure 6.1 Demand Elasticity and the Segmented Markets Model

6.1A 6.1B



The demand for hospital care by privately insured patients, D_p, is downward sloping with a corresponding marginal revenue curve, MR_p. Because hospitals receive a fixed price for treating Medicare patients, the corresponding demand curve, $P_g = MR_g$, is horizontal. The profit maximizing hospital will treat Q_p privately insured patients at a price of P_p. Beyond Q_p, MR_p is less than the fixed Medicare rate. At this point the hospital will accept Medicare patients until the marginal cost of treating these patients equals the Medicare reimbursement rate for a total output of Q_{p+g}. Assume demand in Figure 6.1B is more elastic than demand in Figure 6.1A, perhaps because of differing concentration levels. Hospitals facing more elastic demand will treat more privately insured patients at a lower price,[17] but accept fewer Medicare patients.[18,19]

Figure 6.1A may be more illustrative of Florida hospital markets while Figure 6.1B may be more representative of California hospital markets. There is more managed care penetration in California than in Florida which increases the degree of price competition in California relative to Florida. Although enrollment in Florida HMOs increased 10.7 percent over 1992-1993, as of 1993, only 18.3 percent of the state's population was enrolled in an HMO. Notice that this is substantially less than both the California penetration percentage of 36.4 percent and the national average of 19.4 percent [Marion Merrell Dow (1994)].

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[17] P_p in Figure 6.1B is less that P_p in Figure 6.1A.

[18] The difference between Q_p and $Q_p + Q_g$ represents the quantity of government patients that the hospital treats. This difference is larger in Figure 6.1A.

[19] The price charged to privately insured patients would be even lower in the absence of Medicare and Medicaid patients. In a profit-maximizing hospital a rate reduction by Medicare will not increase the price charges to privately insured patients [Morrisey (1994)].

The difference in HMO penetration may explain the relative changes in hospital net margins in the two states over the respective sample periods. Dranove, *et al.* (1993) find that margins hospitals in their sample earn decline significantly ($p < .01$) from .165 in 1983 to .045 in 1988. This decline occurs because net prices increase only 16.89 percent while costs increase 33.8 percent over their sample period.[20]

The net margin Florida hospitals earn, by contrast, increases over the sample period, from .2846 in 1990 to .3067 in 1993 because of a 9.39 percent increase in net prices. Costs, however, increase only 6.7 percent. As Figure 6.1A illustrates, Florida hospitals appear to have shifted their capacity to serve a higher percentage of Medicare patients. The decision by Florida hospitals to shift capacity and treat more Medicare patients implies that the Medicare reimbursement rate equals or exceeds hospital marginal cost in Florida.

The coefficients on the patient mix (MCARESH, MCAIDSH) and ownership interaction terms (PRMCARE, NPRMCARE, PRMCAID, NPRMCAID) from Table 6.2, column three, are consistent with the pattern of behavior that Figures 6.1A and 6.1B predict. For all ownership classes an increase in the percentage of Medicare patients will increase net margin.[21] Researchers commonly interpret a positive coefficient on the

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[20] Notice that costs increase significantly in spite of the high percentage of the population in managed care networks. This result implies that although managed care networks increase price competition among hospitals, they are not as effective at controlling utilization. Utilization actually may increase because the out of pocket expense to the patient is commonly less in a managed care setting as compared to a coinsurance arrangement. The Rand medical insurance experiment reports that those with lower out of pocket costs consume more medical care. It is also possible that a network hospital will move up its average cost curve as the insurer "steers" patients to network providers .

[21] Recall, as Section III discusses, that the effect of Medicare patients on the margins of non-profit hospitals is the sum of MCARESH and NPRMCARE. Similarly for for-profit hospitals, the total effect is the sum of MCARESH and PRMCARE.

percentage of Medicare patients in the net margin equation as evidence that hospitals shift costs [Dranove, *et al.* (1993)]. The result that the margins of for-profit hospitals increase given an increase in the percentage of Medicare patients, though, contradicts the cost shifting argument. By definition, a for-profit hospital cannot shift costs because to do so the hospital previously must have been charging less than the profit-maximizing price [Morrisey (1994)].

Figures 6.1A and 6.1B, then, illustrate the trade-off inherent in increasing price competition in the private sector. Assuming that hospital markets with a large managed care presence are more competitive than those without such a presence,[22] the private demand for hospital services will be more elastic. Figure 6.1B illustrates that these hospitals will charge lower net prices to privately insured patients, but they will treat fewer government insured patients. As hospitals consolidate in response to managed care growth, the hospital market becomes more concentrated, and demand elasticity declines. Figure 6.1A demonstrates that under these conditions, the hospital's share of government insured patients will increase[23] as will the price charged to privately insured patients.

[22] This is a reasonable assumption because managed care is supposed to increase price competition among hospitals. Eisert (1995) also makes this assumption in her analysis of the factors that affect the quantity of Medicaid patients a hospital serves.

[23] Eisert (1995) makes this argument in her analysis of the effect of competition in the private sector on a hospital's share of Medicaid patients. In contrast to the results that Figures 6.1A and 6.1B imply, she finds that the Herfindahl index has no effect on the hospital's share of Medicaid patients. Her results may be misleading, however, because she bases her geographic markets on statistical metropolitan areas rather than patient flow data. She also excludes large MSA's, defined as having populations greater than one million, as well as rural hospitals from her sample.

V. Tables

A. Table 6.1

Definition of variables

Variable	Definition
NMARGIN	The net margin that a hospital earns on a market basket of services.
HOCCUP	The hospital occupancy rate.
HITECH	The number of technologically advanced services a hospital offers.
MCARESH	The percentage of Medicare patients.
MCAIDSH	The percentage of Medicaid patients.
KSHARE	The percentage of PPO and HMO patients.
CASE	The hospital's annual case-mix score.
CAPINTEN	Hospital capital intensity.
PROFIT, NOPROFIT	Dummy variables indicating ownership status. Government hospitals are the excluded category.
DUM91, DUM92, DUM93	Dummy variables indicating 1991, 1992, and 1993, respectively.
PRMCARE, PRMCAID	The Medicare, and Medicaid percentages of for-profit hospitals, respectively.
NPRMCARE, NPRMCAID	The Medicare and Medicaid, percentages of non-profit hospitals, respectively.
POCCUP, NPOCCUP	The occupancy rates of for-profit and non-profit hospitals, respectively.
ADJMS	Hospital market share adjusted for common ownership.
ADJHHI	The hospital specific Herfindahl index adjusted for common ownership

Table 6.1, continued

Variable	Definition
MSTECH	ADJMS * HITECH
MSK	ADJMS * KSHARE
MSCAP	ADJMS * CAPINTEN

B. Table 6.2

Equation (6.1) with ownership interactions; Dependent variable: Net margin

Regressors ↓	(1) Estimated coefficient	(1) t-ratio (p-value)	(2) Estimated coefficient	(2) t-ratio (p-value)
Constant	.0345	.498 (.6187)	-.0437	-.641 (.5218)
Profit	.0651**	2.551 (.0107)	.0702***	2.84 (.0045)
Noprofit	.0700***	3.157 (.0016)	.0752***	3.419 (.0006)
Hoccup	.0002	.397 (.6911)	.0005	.984 (.3250)
Hitech	.0069	1.341 (.1799)	.0100**	2.029 (.0425)
Case	-.0367	-.737 (.4609)	-.0105	-.213 (.8316)
Mcaresh	.0034***	4.852 (.0000)	.0030***	4.38 (.0000)
Mcaidsh	.0010	.703 (.4821)	.0007	.485 (.6273)
Kshare	.0002	.164 (.8699)	.0007	.617 (.5374)
Adjhhi			.22E-04***	4.782 (.0000)
Adjms	.0012***	2.645 (.0082)		
Capinten	.43E-04	.787 (.4314)	.69E-05	.127 (.8992)
Dum91	.0145	.65 (.5160)	.0160	.738 (.4604)
Dum92	-.0040	-.175 (.8611)	-.0039	-.171 (.8646)
Dum93	.0028	.124 (.9016)	.0027	.123 (.9019)
Diagnostics				
Adjusted R^2	.0608		.0807	
λ^2	124***		140***	
(d.f)	(13)		(13)	
F-ratio (p-value)	4.68*** (.0001)		5.99*** (.0000)	

B. Table 6.2, continued

Regressors ↓	(3) Estimated coefficient	t-ratio (p-value)	(4) Estimated coefficient	t-ratio (p-value)
Constant	-.5185***	-3.528 (.0004)	-.6000***	-4.171 (.0000)
Profit	.7101***	4.495 (.0000)	.7201***	4.693 (.0000)
Noprofit	.6267***	3.992 (.0001)	.6219***	4.089 (.0000)
Hoccup	.0049***	4.155 (.0000)	.0053***	4.738 (.0000)
Hitech	.0060	1.122 (.2620)	.0090*	1.773 (.0763)
Case	-.0682	-1.325 (.1852)	-.0411	-.810 (.4179)
Mcaresh	.0083***	4.862 (.0000)	.0077***	4.623 (.0000)
Mcaidsh	.0086***	3.396 (.0007)	.0083***	3.351 (.0008)
Kshare	.0006	.476 (.6340)	.0011	.963 (.3356)
Adjhhi			.24E-04***	4.825 (.0000)
Adjms	.0013***	2.805 (.0050)		
Capinten	.31E-04	.612 (.5405)	-.57E-05	-.111 (.9115)
Dum91	.0162	.743 (.4573)	.0177	.840 (.4009)
Dum92	-.0014	-.061 (.9513)	-.0013	-.058 (.9538)
Dum93	.0045	.201 (.8408)	.0042	.191 (.8484)
Poccup	-.0056***	-3.896 (.0001)	-.0060***	-4.283 (.0000)
Npoccup	-.0049***	-3.842 (.0001)	-.0048***	-3.881 (.0001)
Prmcare	-.0050***	-2.726 (.0064)	-.0047***	-2.633 (.0085)
Nprmcare	-.0041**	-2.208 (.0273)	-.0039**	-2.158 (.0309)

B. Table 6.2, continued

Regressors ↓	(3) Estimated coefficient	t-ratio (p-value)	(4) Estimated coefficient	t-ratio (p-value)
Prmcaid	-.0090**	-2.480 (.0131)	-.0089**	-2.521 (.0117)
Nprmcaid	-.0073**	-2.520 (.0118)	-.0076***	-2.624 (.0087)
Diagnostics				
Adjusted R^2	.0775		.09981	
λ^2	144***		162***	
(d.f)	(19)		(19)	
F-ratio	4.27***		5.31***	
(p-value)	(.0000)		(.0000)	

Notes: I use the White estimator to obtain the correct asymptotic covariance matrix based on the value of the λ^2 statistic. Notice that '*,' '**,' and '***' indicate significance at the 10%, 5%, and 1% levels, respectively.

C. Table 6.3

**Equation (6.1) with market share interactions;
Dependent variable: Net margin**

Regressors ↓	(1) Estimated coefficient	(1) t-ratio (p-value)	(2) Estimated coefficient	(2) t-ratio (p-value)
Constant	.0372	.548 (5838)	-.5132***	-3.443 (.0006)
PROFIT	.0731***	2.870 (.0041)	.6844***	4.292 (.0000)
NOPROFIT	.0747***	3.335 (.0009)	.6173***	3.878 (.0001)
HOCCUP	.0001	.202 (.8396)	.0045***	3.919 (.0001)
HITECH	-.0146*	-1.902 (.0571)	-.0161**	-1.961 (.0499)
KSHARE	.0006	.460 (.6456)	.0007	.464 (.6425)
MCARESH	.0030***	4.268 (.0000)	.0078***	4.473 (.0001)
MCAIDSH	.0011	.725 (.4687)	.0111***	4.208 (.0000)
CAPINTEN	.0002*	1.696 (.0900)	.0001	1.470 (.1416)
CASE	-.0106	-.213 (.8315)	-.0500	-.980 (.3271)
ADJMS	.0007	.985 (.3245)	.0005	.803 (.4220)
MSK	-.2E-04	-.331 (.7406)	.3E-04	.494 (.6216)
MSTECH	.0008***	4.327 (.0000)	.0008***	3.914 (.0001)
MSCAP	-.4E-05**	-2.482 (.0131)	-.3E-05**	-2.385 (.0171)
POCCUP			-.0050***	-3.665 .0003)
NPOCCUP			-.0043***	-3.344 (.0008)
NPRMCARE			-.0039**	-2.070 (.0384)
PRMCARE			-.0045**	-2.417 (.0156)
NPRMCAID			-.0102***	-3.298 (.0010)
PRMCAID			-.0113***	-3.057 (.0022)

Table 6.3 continued

Regressors ↓	(1)		(2)	
	Estimated coefficient	t-ratio (p-value)	Estimated coefficient	t-ratio (p-value)
DUM91	.0151	.690 (.4901)	.0195	.900 (.3679)
DUM92	-.0029	-.124 (.9012)	.0024	.104 (.9172)
DUM93	.0045	.197 (.8440)	.0097	.433 (.6649)
Diagnostics				
Adjusted R^2	.0693		.0915	
F-ratio (p-value)	4.42*** (.0000)		4.38*** (.0000)	
λ^2 (d.f)	147*** (16)		162*** (22)	

Notes: I use the White estimator to obtain the correct asymptotic covariance matrix because of the value of the λ^2 statistic. Notice that '*,' '**,' and '***' indicate significance at the 10%, 5%, and 1% levels, respectively.

D. Table 6.4

A comparison of hospital competition, by selected criterion: Florida and California

	Florida	California	
Selected Characteristics ↓	**1990-1993**	**Dranove, *et al.* (1993)**	**Melnick, *et al.* (1992)**
Cross Section Regression Results			
Net Margin Equation			
Herfindahl Index	.22E-04** , .24E-04**	.073**, .13***[a]	NA
Market Share	.0012**, .0013*	NA	NA
Net Price Equation			
Herfindahl Index	.0109**	509*, 496*	.1021**, .1375**
Market Share	-.1463		
Geographic Market Definition	Patient discharge data	Urbanized areas and population centers of > 5,000	Patient discharge data
Descriptive Statistics			
Mean Net Margin			
Beginning	.2846	.165	NA
Ending	.3067	.045	NA
% Change	7.77	-72.73	NA
Mean Net Price			
Beginning	903.61	7242	.917
Ending	988.42	8465	NA
% Change	9.39	-16.89	NA
Mean Average Cost			
Beginning	617.84	5888	NA
Ending	659.21	7879	NA
% Change	6.70	33.81	NA
Mean Medicare Share			
Beginning	54.30	46.7	32.1
Ending	57.91	32.6	NA
% Change	6.65	-30.19	NA

Table 6.4 continued

	Florida	**California**	
Selected Characteristics ↓	**1990-1993**	**Dranove, *et al.* (1993)**	**Melnick, *et al.* (1992)**
Mean Herfindahl Index			
Beginning	2684	2390	3320
Ending	2801	2560	NA
% Change	4.36	7.11	NA
Sample	185 Florida S-T general hospitals	292 S-T California general, govt. hospitals excluded	190 hospitals in the Blue Cross of CA network

Notes: I take the Florida net margin cross section results from Table 6.2. I do not report the Florida net price cross section results in earlier chapters. The Dranove, *et al.* (1993) results refer to their 1988 data. The mean net price differs substantially among the three studies because of their respective constructions. The market basket in Dranove, *et al.* (1993) contains different services than the services I use here. Melnick, *et al.* (1992) use a relative price index for their price variable. The Herfindahl index reflects the common ownership of multi-hospital systems. Notice that '*,' '**,' and '***' indicate significance at the 10%, 5%, and 1% levels, respectively. An entry of "NA" indicates that the paper does not provide this information.

CHAPTER SEVEN

Summary

This dissertation uses several methods to ascertain the nature of the relationship between hospital price-cost margins and market structure. Recall that there are two interpretations of the finding that hospital margins are higher in more concentrated markets. According to the structure-conduct-performance paradigm, margins are higher in more concentrated hospital markets because concentration facilitates successful collusion. Demsetz (1973, 1974), by contrast, argues that margins are higher in more concentrated markets because large market share firms have lower costs arising from their superior efficiency.

To distinguish between these competing hypotheses, I estimate conjectural elasticities for 185 hospitals using panel data from Florida hospitals over 1990 to 1993 and test for competitive, collusive, and Cournot behavior, respectively. Recall that under a Cournot equilibrium, equation (2.7) predicts a positive relationship between a hospital's market share and its price-cost margin. Such a result is consistent with the efficiency hypothesis. The more efficient hospitals will have higher margins, and because of their efficiency, they will acquire large market shares, thereby increasing the level of concentration in the market. Conversely, if the perfectly collusive outcome prevails, the estimated conjectural elasticity is equal to one and equation (2.7) predicts no relationship between hospital market share and price-cost margin.

Not surprisingly, the majority of hospitals have market power over price. I reject competitive behavior, indicated by a conjectural elasticity equal to negative one, for approximately 84 percent of Florida hospitals. Instead, Florida hospitals appear to engage in some cooperative behavior. I reject Cournot behavior for 76 percent of the sample. This widespread departure from Cournot behavior implies that Florida hospitals compete primarily on quality. The large Medicare population in Florida supports this hypothesis. Because hospitals do not negotiate Medicare reimbursement rates, quality is the only dimension along which hospitals can compete for these patients. Quality competition may become less important, however, as Medicare managed care networks continue to grow. Increased price competition may not lower payor costs significantly in Florida, however, because increased demand from a growing Medicare population has the potential to fill hospital excess capacity [Murray and Anderson (1996)].

The most interesting result from the tests for a Cournot equilibrium is that hospitals that do not follow Cournot behavior are located in somewhat less concentrated markets than are those hospitals that adopt Cournot behavior. This relationship between market structure and departure from Cournot behavior indicates that hospitals in less competitive (more concentrated) hospital markets do not expect rival hospitals to respond to their output choices. Such a result implies that hospitals in more concentrated markets ignore departures from any collusive agreements. Stigler (1964) argues, by contrast, that cooperative arrangements are easier to monitor and enforce in concentrated markets.

Alternatively, this result may be indicative of an information based model of hospital competition, which Satterthwaite (1979) introduces. In his model, reductions in concentration actually lead to less competition in a market for "reputation" goods.[1] This unexpected result occurs because as competition increases, search becomes more costly for consumers. In response to the increased search cost, consumers investigate fewer firms, so that competition actually decreases.

I reject perfect coordination of hospital decisions, reflected in a conjectural elasticity equal to one, for only 21 percent of hospitals in the sample. Because collusion to restrict output below the competitive level is unlikely in an industry with excess capacity, it is plausible that this result documents the hospitals' similar efforts to reduce the excess capacity that the cost containment initiatives of both private and public payors create. Because federal hospital merger policy is not well-defined, hospitals engage in joint ventures to reduce the under-utilization of expensive equipment [Magleby (1996)]. Joint ventures have the additional advantages of maintaining hospital autonomy and reducing managerial conflicts [Campbell (1996)]. Most important, the Florida legislature provides immunity from antitrust investigation for approved kinds of hospital cooperative behavior [Magleby (1996)].

The results of the probit regressions[2] also indicate that a failure to reject the hypothesis that a hospital's estimated conjectural elasticity is equal to one reflects joint

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[1] For a reputation good, products are differentiated and quality is consumer specific. Furthermore, consumers can only evaluate quality over time [Satterthwaite (1979)].

[2] Recall that I estimate two probit equations with the dependent variables as equations (5.2a) and (5.2b) describe. These dependent variables identify cooperative behavior.

venture activities among Florida hospitals, and not explicit attempts to restrict output below the competitive level. Most important, this analysis reveals that market structure does not have the expected effect on hospital behavior. In contrast to the structure-conduct-performance paradigm, I find that market concentration actually reduces the likelihood of collusion. Instead, small, rural hospitals are most likely to collude. This result may imply that cooperative behavior is necessary for small, rural hospitals to survive in a managed care environment. Indeed, joint ventures to reduce capacity may be more feasible for rural hospitals than a merger because rural hospitals are often the largest employers in an area [Campbell (1996)].

Collaborative ventures will reduce the excess capacity in Florida hospital markets and increase the level of market concentration. A reduction in capacity would help to ensure that hospitals do not stop providing essential services because of under-utilization. Indeed, I find that the provision of technologically advanced services becomes profitable only as a hospital captures a greater share of the market, presumably because of the high fixed costs associated with such services.

The increase in hospital concentration, moreover, will not necessarily erode a payor's bargaining position. Most important, price function regressions reveal that hospital behavior has no impact on the prices that a hospital receives. I find no evidence, furthermore, that increased market concentration results in higher hospital prices. The presence of a dominant hospital in a market, similarly, does not create an umbrella under which other hospitals in that market can earn economic rent by charging higher prices. The overall effects of market share on hospital prices are small. The magnitude of the

significant coefficients in the net price equation suggests that a hospital's case mix index, not its market share, is the most important determinant of its net price. Even if hospitals enjoy a superior bargaining position in managed care negotiations, any price effects to the actual purchasers of health insurance depend on the extent of competition among health insurance plans. From this perspective, the outcome of the bargaining game between the third-party payor and the hospital represents a redistribution of profit between upstream and downstream suppliers.[3]

Concentrated hospital markets will also allow Florida hospitals to minimize costly non-price competition. Because Florida hospitals have a large Medicare base, they currently engage primarily in non-price competition. Earlier research on hospital competition shows that, under non-price competition, hospitals in less concentrated markets have higher costs [Robinson and Luft (1985, 1987, 1988), Noether (1988)]. Although the formation of Medicare HMOs may increase the importance of price competition among Florida hospitals, the reduction in excess hospital capacity should not prevent the Health Care Financing Association (HCFA) from lowering its cost of providing health insurance to an expanding Medicare population. In the most common variety of Medicare HMO, a risk-based model, the outcome of the bargaining game between the hospital and the supplier will be solely a redistribution of profit, because the reimbursement that the HMO receives from HCFA is a non-negotiable, capitated amount equal to the average per-capita cost that Medicare pays in the pertinent geographic area.[4]

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[3] In this scenario the third-party payor supplies the insured with the product "insured medical care." The third-party payor then contracts with both physicians and hospitals. The obvious exception is an HMO that both owns its own hospital and actually employs physicians.

[4] Murray and Anderson (1996) provide a description of the various kinds of Medicare HMOs.

The results in this dissertation indicate that federal and state antitrust authorities should allow Florida hospitals to continue to reduce their excess capacity through merger and joint venture. Protection from federal antitrust prosecution under the Florida Hospital Cooperation Act should facilitate this effort. Replicating these analyses using a longer, multi-state panel data set and controlling explicitly for quality differences among hospitals would confirm the findings of this study.

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